A comprehensive evaluation of macroeconomic forecasting methods*

Andrea Carriero — Queen Mary University of London

Ana Beatriz Galvao† — University of Warwick

George Kapetanios — King's College London

August, 2018

Abstract

By employing datasets for seven developed economies and considering four classes of multivariate forecasting models, we extend and enhance the empirical evidence in the macroeconomic forecasting literature. The evaluation considers forecasting horizons from one-quarter up to two-years ahead. We find that the structural model, a medium-sized DSGE model, provides accurate US and UK long-horizon inflation forecasts. To strike a balance between being comprehensive and producing clear messages, we employ meta-analysis regressions to 2,976 relative accuracy comparisons that vary with forecasting horizon, country, model class and specification, number of predictors, and evaluation period. For point and density forecasting of GDP growth and inflation, we find that models with a large number of predictors do not perform better than models with 13-14 hand-picked predictors. Factor-augmented models and equal-weighted combinations of single-predictor mixed-data sampling regressions are a better choice for dealing with a large number of predictors than Bayesian VARs.

Keywords: factor models, BVAR models, MIDAS models, DSGE models, density forecasts, meta analysis.

JEL codes: C53

*All three authors acknowledge support for this work from the Economics and Social Research Council [ES/K010611/1]. We also are grateful to our research assistant Katerina Petrova, who was also funded by the ESRC, for excellent assistance.

†Corresponding author: Ana Galvao, Economic Modelling and Forecasting Group - Warwick Business School, University of Warwick, Coventry, CV4 7AL, UK. ana.galvao@wbs.ac.uk.

1 Introduction

Forecasting is one of the major aims of economic and econometric analysis along with modelling the foundations of economic phenomena. As a result, considerable efforts have been made in academic work to lay the foundations and build tools for efficient forecasting.

The macroeconomic forecasting literature can be divided into two broad categories. The first aims to produce models that attempt to explain the economy first and then provide forecasts only as a byproduct of their main aim. This is, in principle, optimal in the sense that a model which can explain successfully the economy should be able to forecast well. Nevertheless the complexity of the economy and of the models that are needed for its full explanation implies that such forecasts might not be accurate in sample, let alone out of sample.[1] The second stream of research considers models that do not attempt a full structural modelling but simply a reduced-form statistical description. These models frequently have superior forecasting performance, but their reduced-form nature makes it harder to provide economic storytelling to support forecasts. This characteristic is classified as a relevant disadvantage by many economists and policymakers.

This has not stopped the proliferation of reduced-form models and a rapid rise in their sophistication. Recent trends in this literature include modelling structural changes and the efficient use of increasingly larger datasets. The former has been driven by the widespread recognition that structural change is a leading cause of forecast failure. A number of approaches of varying sophistication are being used to accommodate structural change. These range from time-varying coefficient models to methods that allow for time varying estimation of standard econometric forecasting models. In this context, as is common with forecasting in general, increasing sophistication has not been found to necessarily correlate closely with superior forecasting performance.[2] The second trend of considering large datasets has been spurred by their use in many economic analyses, given their availability in central banks and other policy making institutions.[3]

[1] For example, Faust and Wright (2013) and Chauvet and Potter (2013) conclude their reviews on the forecasting performance of structural and reduced-form models for predicting inflation and output growth arguing that structural models do not have better forecast accuracy than univariate time series models.

[2] For example, Faust and Wright (2013) provide evidence that time-varying vector autoregressive models with stochastic volatility do not improve point forecasts of inflation in comparison with a univariate benchmark, although there is stronger evidence that stochastic volatility improves density forecasts of inflation (Clark, 2011). Chauvet and Potter (2013) consider Markov-Switching models to predict output growth, and they find gains only during recessions and only at short horizons. Based on data for a set of countries, Ferrara, Marcellino and Mogliani (2015) show that nonlinear models rarely improve forecasts of their linear counterpart.

[3] Stock and Watson (2002) is an influential paper supporting the use of large datasets for forecasting macroeconomic variables. Other more recent contributions, all pointing towards the importance of using medium-large dataset for

The above developments set the scene for the current paper. Our aim is to provide a state of the art and comprehensive evaluation of recently proposed model classes for forecasting output growth and inflation, giving special attention to model classes able to deal with a large number of predictors. The aim of the paper is to strike a balance between being comprehensive and producing clear messages. This requires considering a wide range of models but being selective in some dimensions so as to make the evaluation exercise feasible and informative. Further, it requires an evaluation across a number of different countries and different sample periods. Finally, we aim to compare and contrast reduced-form models and structural models, which have traditionally been considered inferior for forecasting purposes. This latter aspect of our analysis is less commonly found in forecasting evaluations.[4]

Forecasting comparisons in the literature focus normally on data from a single country or a small subset of countries (US, UK and Euro Area).[5] We will use instead data from seven economies: US, UK, Euro Area, Germany, France, Italy and Japan. For these seven economies, we compute forecasts for output growth and inflation with three classes of state-or-art reduced-form forecasting models: Factor-Augmented Distributed Lag (FADL) Models, Mixed Data Sampling (MIDAS) Models, Bayesian Vector Autoregressive (BVAR) Models.[6] These model classes are useful to explore the

macroeconomic forecasting, include Bańbura, Giannone and Reichlin (2010), Carriero, Clark and Marcellino (2015), Koop (2013) and Giannone, Lenza and Primiceri (2015).

[4] Density forecasts of DSGE models are evaluated by Del Negro and Schorftheide (2013) and Diebold, Schorftheide and Shin (2017), but when DSGE models are compared with a large set of statistical models in Faust and Wright (2013) and Chauvet and Potter (2013) only point forecasts are considered. Note also that the set of forecasting models for predicting inflation in Faust and Wright (2013) differs from the models in Chauvet and Potter (2013). While Faust and Wright (2013) consider up to one-year-ahead horizons, Chauvet and Potter (2013) choose to look at horizons up to two quarters only, but Del Negro and Schorftheide (2013) evaluate horizons up to two years ahead.

[5] Stock and Watson (2003) and Kuzin, Marcellino and Schumacher (2013) are exceptions by considering data from seven countries when designing their forecasting exercises. Ferrara et al. (2015) evaluate models for 19 countries, but they use only a relatively small set of predictors.

[6] Time-varying vector autoregressive models, expoited as forecasting models by D'Agostino, Gambetti and Giannone (2013), and vector autoregressive models with stochastic volatility, with forecasting performance evaluated by Clark (2011), are classes of models that are excluded from this forecasting comparison. The main reason is that both classes are not easily adaptable to large datasets. The proposed approach by Koop and Korobilis (2013) for large datasets considers a VAR with 25 variables as "large". In this paper, we use datasets up to 155 variables. We also use data from contries with shorter time series where structural changes are harder to identify. In this paper, we consider just one class of mixed frequency models. Mixed frequency specifications are popular for nowcasting as surveyed by Banbura, Giannone, Modugno and Reichlin (2013), including recent contribution by Schorfheide and Song (2015). Because we aim to evaluate forecasting performance from nowcasting up to long horizons (two years), we select just one class of

predictive information of a large number of indicators. As a consequence, we build a dataset with a large number of monthly indicators for each country and assess the importance of employing large (one-hundred predictors) datasets in comparison with medium-sized (a dozen predictors) and small datasets in macroeconomic forecasting. We also consider one class of structural models: a medium-sized Dynamic Stochastic General Equilibrium Model (DSGE). We compare the DSGE performance with reduced-form models for forecasting output growth and inflation in the US, the UK and the Euro area.

We have some knowledge of the relative point forecasting performance of DSGE models with respect to Bayesian VARs (as, for example, Smets and Wouters (2007)), of FADL to Factor-Augmented MIDAS Models (Andreou et al. (2013)), and of Bayesian VARs to Dynamic Factor models (Bańbura et al. (2010)). In this paper, we advance further by comparing the out-of-sample forecasting accuracy for point and density forecasts of output growth and inflation for the following class of models: BVAR, FADL, MIDAS and DSGE models.

The design of our forecasting comparison with the elements described above imply that we evaluate the forecasting performance of 13 reduced-from model specifications to predict two quarterly macroeconomic time series over horizons from one-quarter to eight-quarters ahead. And we do this comparison for seven different countries and consider four different subperiods of 5 years over a 20 year out-of-sample period. In order to get clear messages from our empirical exercise, we develop evaluation methods that pool forecasting performance across countries, model class, forecasting origin period and dataset size.

Our meta-analysis method employs a regression of the relative performance of each multivariate reduced-form model on a set of characteristics. The relative performance is measured using the root mean squared forecast error for point forecasts and logscores for density forecasts. The performance is measured with respect to the autoregressive model for the same variable and horizon. The method allows us to assess the statistical significance of forecasting horizon, geographical source (country), model class, evaluation period and number of predictors (dataset size) in explaining forecasting performance.

A second evaluation method relies on t-statistics for a Diebold and Mariano (1995) equal forecast accuracy test for the 20-year evaluation period. We investigate the empirical distribution of t-statistics with an autoregressive model under the null. We use this approach to complement the results of the meta-analysis when comparing the point and density forecasting performance of specifications that use a large set of predictors in comparison with the ones that use a smaller set. We also use empirical distributions of equal accuracy t-statistics against an AR benchmark to evaluate

mixed frequency models that has relatively good nowcasting performance (Andreou, Ghysels and Kourtellos (2013) and Kuzin et al. (2013)).

how the structural models forecasting accuracy compares with reduced-form models.

We find no support for the use of large datasets (one-hundred predictors) instead of medium-sized (a dozen predictors) ones. However, we provide evidence that the factor model and an equal-weighted combination of single regressor MIDAS models are the best specifications to deal with large datasets since they perform on average better than Bayesian VARs. We find that DSGE models have relative good performance for forecasting US and UK inflation at forecasting horizons longer than one year.

The empirical results provide only limited support to the use of mixed frequency models, which exploit current quarter information on monthly series, to improve nowcasts of output growth. The reason is that there is large cross-country variation on nowcasting performance of mixed frequency models. The results also suggest changes in the relative forecasting performance of forecasting models. The relative performance of reduced-form multivariate models is at its peak in the 1993-1997 period for inflation and in the 2008-2011 period for output growth.

We describe the classes of forecasting models in Section 2. Section 3 provides a summary of the datasets we employed, which are fully reported in our online appendix. Section 4 describes the key elements of the design of our forecasting exercises, including statistical tests employed. In section 5, we explore the key determinants of point and density macroeconomic forecasting performance of multivariate statistical models to AR models using meta-analysis regressions and the empirical distribution of equal-accuracy t-statistics. An evaluation of the point and density forecasting accuracy of structural models in comparison to reduced-from models is discussed in section 6. Section 7 concludes.

2 Forecasting Methods

In this section, we describe the forecasting methods compared in this paper. In contrast to the recent evaluations on forecasting output and inflation by, respectively, Chauvet and Potter (2013) and Faust and Wright (2013) we use the same set of forecasting model classes for predicting output growth and inflation. The advantage of this approach is that we can evaluate whether we need different forecasting models for output and inflation. The disadvantage is that we do not evaluate forecasting methods that were designed for some specific features of each variables, such as the UCSV models for inflation (Stock and Watson, 2007) and Markov-Switching models for output (Chauvet, 1998). Another important feature of our forecasting exercise is that we consider both point and density forecasts. Density forecasting evaluation provides us with insights on the accuracy of forecasting models for the whole predictive distribution. The advantage of considering both point and density forecasts is that we can assess whether the choice of loss function has an impact on model rankings.

In the remainder of this section we describe how we compute density forecasts of three reduced-form forecasting models: Factor models, Bayesian VAR models and MIDAS models. We also describe how we obtain density forecasts using a structural DSGE model, and simple univariate models.

In the text bellow, we use the following notation. Q_t for $t = 1, ..., T$ denotes the raw data; and $q_t = \log(Q_t)$ denotes the time series in log-levels. The variable in first differences is $\Delta q_t = 100 * (q_t - q_{t-1})$. A forecast horizon is h, and the maximum forecast horizon is $h_{\max}$.

2.1 Univariate Models

We compute forecasts from univariate autoregressive (AR(p)) models. The autoregressive order is selected using the Schwarz (SIC) information criterion and assuming maximum order of 4. We compute the predictive density by bootstrap as in Clements and Taylor (2001). First, we get a full bootstrapped time series $\Delta q^*_{p+1}, ..., \Delta q^*_T$ by using the OLS estimates, initial values $\Delta q_1, ..., \Delta q_p$ and a $T-p$ bootstrapped time series from the residuals. Using the bootstrapped time series, we estimate an AR(p) model with the same autoregressive order as the original model. Then we compute forecasts by iteration for $h = 1, .., h_{\max}$ including a bootstrap draw from the residuals for each horizon. This bootstrap procedure will deliver sequential draws as $\Delta \hat{q}^{(i)}_{T+1}, ..., \Delta \hat{q}^{(i)}_{T+h_{\max}}$ for each time we reestimate the model on a new bootstrapped sample.

2.2 Factor Models

We forecast with factors using the following FADL(p,k) equation for each horizon h:

$$\Delta q_t = \beta_0 + \sum_{i=0}^{p-1} \beta_{i+1} \Delta q_{t-h-i} + \sum_{j=1}^{r} \sum_{i=0}^{k-1} \gamma_{j,i+1} f_{j,t-h-i} + \varepsilon_t, \tag{1}$$

where r counts the number of factors f.

Factors are estimated by principal components applied to either a medium (around 14 variables) or large (around 100 variables) dataset of predictors of q_t. Before the factor estimation, we decide on whether transforming raw data to log-levels as described in the "log vs level" column in Tables B2 and B3 in the online appendix. Then we apply ADF unit root tests to define the order of differentiation of each variables. Principal components is then applied to standardized data to compute the factors. We follow Groen and Kapetanios (2013) to choose the number of factors. We first choose the autoregressive order p in a univariate regression using the SIC, then we set $k = 1$ to choose the number factors using Groen and Kapetanios (2013) modified SIC assuming a maximum number of factors of 4. We have also tried to jointly choose r and k using the modified SIC, and normally $k = 1$ is the choice indicated, and even when q should be larger, the impact on average forecasting performance is negligible.

We compute density forecasts from the FADL model by fixed regressor bootstrap. We choose this specific approach because it takes into account both parameter and forecasting uncertainties when computing density forecasts, and because we will apply a similar approach, based on Aastveit, Foroni and Ravazzolo (2016), to compute density forecasts with MIDAS models. This implies that we fix the variables in the right-hand side (RHS) of the regression to their data values, and use bootstrapped values from the residuals to get a full bootstrapped time series $\Delta q^*_{p+1}, ..., \Delta q^*_T$ for the left-hand side (LHS).[7] Then we re-estimate the ADL regression using the bootstrapped LHS values and the fixed RHS values. Using bootstrapped coefficients, we compute a forecast draw $\Delta \hat{q}^{(i)}_{T+h}$,conditional on observed values for $..., \Delta q_{T-1}, \Delta q_T$, and using a bootstrap draw from the reestimated regression residuals. Note that this bootstrapping procedure will deliver the density for one specific forecasting horizon. Our factor modelling approach requires the estimation of a forecasting model for each horizon.

2.3 MIDAS Models

The economic predictors in our dataset, summarized in Table 2, are sampled monthly. The factor approach described above requires the aggregation of monthly data into quarters. We directly exploit monthly information employing an ADL-MIDAS model. The model is written as:

$$\Delta q_t = \beta_0 + \sum_{i=0}^{p-1} \beta_{i+1} \Delta q_{t-h-i} + \gamma \sum_{i=0}^{km-1} w(\theta, i) x_{t-mh-i+l} + \varepsilon_t,$$

where m is the difference in sampling frequency between q_t and x_t, and $w(\theta, i)$ are the weights for each high frequency lag, which are a function of the parameters θ. In our applications $m = 3$ since x_t is sampled monthly while q_t is sampled quarterly. The autoregressive order in quarters is denoted by k, and km is the autoregressive order in months such that lags of x are counted in months. The number of lead months is represented by l (named as in Andreou et al. (2013), but first employed for macroeconomic forecasting by Clements and Galvão (2008)). The intuition on the use of leads is that forecasts for current and future quarters are computed conditional on monthly observations of economic indicators during the current quarter. In the forecasting exercise, we set $l = 2$ for all h. This implies that we are considering typical nowcasting horizons if $h = 1$. This utilization of monthly data is the main advantage of the MIDAS approach for macroeconomic forecasting (Clements and Galvão, 2008; Kuzin et al., 2013; Andreou et al., 2013).

To measure the impact of the high frequency x_t on the low frequency q_t we first apply the weights $w(\theta, i)$ to all monthly lags, then we multiply by an intercept γ, which is identified because the weights

[7] As a consequence, this approach does not take into account the uncertainty on the estimation of the factors, but only on the β_s and γ_s.

sum up to one. We use the beta function to obtain the weights, that is,

$$w(\theta; i) = \frac{f(\theta; i)}{\sum_{j=1}^{K} f(\theta; j)}$$
$$f(\theta; i) = \frac{(j)^{\theta_1 - 1}(1-j)^{\theta_2 - 1}\Gamma(\theta_1 + \theta_2)}{\Gamma(\theta_1)\Gamma(\theta_2)}; \quad j = i/km.$$

The two parameters in θ are jointly estimated with the other parameters by nonlinear least squares. Note that, as in the case of the factor approach, we need to estimate a MIDAS regression for each forecasting horizon.

We compute density forecasts by fixed regressor bootstrapped as in Aastveit et al. (2016) and as described in section 2.2. Our application of the fixed regressor bootstrap to MIDAS models implies that we also fix θ, that is, take $\theta = \hat{\theta}$ from the estimation with observed data, and we obtain different values of β_i and γ for each bootstrapped sample. This has a large beneficial impact on our computational burden. Our density computation strategy is still able to capture the impact of parameter uncertainty on a set of parameters while computing forecasts. Note that, as in the case of factor models, the last step to compute $\Delta\hat{q}_{T+h}^{(i)}$ requires also a draw from the residuals of the re-estimated MIDAS regression.

We consider two different types of MIDAS specifications that are able to deal with large datasets. The first one assumes that x is an individual predictor. Because we plan to employ sizeable datasets, we estimate a single regressor MIDAS models for each predictor, then we combine their predictive densities using equal weights. We call this model the combination MIDAS (C-MIDAS) model. In this specification, we decide beforehand whether we will be using log, log-levels or quarterly differences for each one of the indicators when using our medium dataset. Our choice of data transformation is indicated in Tables B2 and B3 in the online appendix.

The second specification estimates factors with monthly data by principal components applying the data transformation based on unit root tests described for FADL models. Then we set the number of factors to one in the case of medium datasets and to two in the case of large datasets following Andreou et al. (2013). We call this specification the F-MIDAS model, and the regressors x_t are factors estimated in a previous step by principal components

2.4 BVAR Models

Our BVAR approach is the benchmark model of Carriero et al. (2015), who provide a summary the literature on the application of BVARs for forecasting. Define the vector: $y_t = (q_{1t}, q_{2t}, ..., q_{Nt})'$, then a VAR(p) is:

$$y_t = A_0 + A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t \tag{2}$$

$$\varepsilon_t \sim N(0, \Sigma)$$

for $t = p+1, ..., T$.

We elicit a conjugate Normal-Inverse Wishart prior:

$$\alpha|\Sigma \sim N(\alpha_0, \Sigma \otimes \Omega_0)$$

$$\Sigma \sim IW(S_0, v_0),$$

where $\alpha = vec([A_c, A_1, ..., A_p]')$, so the posterior distributions are

$$\alpha|\Sigma, data \sim N(\overline{\alpha}, \Sigma \otimes \overline{\Omega})$$

$$\Sigma|data \sim IW(\bar{S}, \bar{v}).$$

Carriero et al. (2015) describe the close form solutions for the posterior means and variances, and the prior mean and variances under the assumption that they follow a Minnesota-style prior as in Bańbura et al. (2010). We consider prior means for the first-order autoregressive coefficients equal to one if the endogenous variables, y_t, are in log-levels as described above. We also consider a specification in differences, using Δy_t, with the prior mean equal to zero.

We also impose -in the case of VAR in levels- the sum of coefficients prior, which expresses the belief that the average of the past values of a given variable provides a good forecast for that variable. The fact that, in the limit, the sum-of-coefficients prior is not consistent with cointegration motivates the use of an additional prior, known as the 'dummy initial observation' prior. This was proposed by Sims (1993) and avoids giving an unreasonably high explanatory power to the initial conditions, a pathology which is typical in nearly nonstationary models (Sims, 2000). These last two priors together tend to improve forecasts when dealing with data in levels. Hyperparameters governing priors are set as the baseline case in Carriero et al. (2015). The overall prior tightness λ_1 is selected to maximise the marginal likelihood:

$$\lambda_1 = \arg\max_{\lambda_1} \ln(p(Y)),$$

where $p(Y)$ is computed in close form as in Carriero et al. (2015). The grid has 15 elements [0.01, 0.025, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.75, 1, 2, 5]. In an out-of-sample forecasting exercise, we compute λ_1 at each time we re-estimate the model with a longer sample period.

Forecasts are computed by simulation. We use posterior draws of α and Σ to obtain a implied path for $\hat{y}_{T+1}, ..., \hat{y}_{T+h}$. Assume that $\mathbf{A} = [A_c, A_1, ..., A_p]'$ that is a $N \times Np + 1$ matrix , then we obtain a draw j for all autoregressive coefficients using:

$$(\mathbf{A}^{(j)}) = (\overline{\mathbf{A}}) + chol(\overline{\Omega}^{(j)}) * V^{(j)} * chol(\mathbf{\Sigma}^{(j)})',$$

where $V^{(j)}$ is $(Np+1) \times N$ matrix obtained from a standard normal distribution. Then for a draw of $\mathbf{A}^{(j)}$ and $\mathbf{\Sigma}^{(j)}$, we draw a sequence of h draws from the $N(0, \mathbf{\Sigma}^{(j)})$ to compute by iteration a sequence of forecasts $\hat{y}_{T+1}, ..., \hat{y}_{T+h}$ for model (2). We use a total 5000 draws, and the procedure is split such that we use a few number of draws of $\mathbf{A}^{(j)}$ and $\mathbf{\Sigma}^{(j)}$, and then for each parameter draw, we generate many sequences of forecasts. The point forecast is the median over all draws for each horizon.

We consider specifications in levels, and we call L-BVAR, and in differences, called D-BVAR. We set $p = 4$. When the target forecasting variable is the quarterly growth rate, we transform accordingly the forecasts for the model in levels.

2.5 DSGE Models

The literature provides evidence of accuracy of the medium-sized Smets and Wouters (2007) model (Christoffel, Coenen and Warne, 2010; Edge and Gurkaynak, 2011; Del Negro and Schorftheide, 2013; Woulters, 2015). We employ the Smets-Wouters DSGE model with seven observables, including output and inflation as our structural model. We use the specification in Smets and Wouters (2007) and Herbst and Schorftheide (2012), which assume a deterministic trend to productivity.

We use the priors as in Smets and Wouters (2007) and Herbst and Schorftheide (2012). The posterior distribution of the structural parameters is obtained by the Random Walk Metropolis Algorithm described in Del Negro and Schorftheide (2011), and we calibrate the spread parameter such that the acceptance rate is in the 20-40% range for each country dataset. We use 5000 equally-spaced draws from the kept posterior parameters draws generated by the MCMC procedure to compute the predictive density. For each parameter draw, we also draw from the normal distribution of the disturbances (structural shocks) to get a sequence of forecasts from $h = 1,...,h_{\max}$ for each observed variable.

We compute forecasts with DSGE models for only three countries in our dataset: US, UK and Euro Area. The reason is that the assumption in the model that the central bank that sets interest rates based on a Taylor rule, which depends on domestic inflation, is not adequate to countries which are part of the Euro Area. We also choose not apply to Japan, again because the Taylor rule may be a very poor approximation of Bank of Japan monetary policy in the last 20 years. To apply the model to Euro area data, we add an equation linking employment to hours such that we can use the employment time series instead of hours, following the modification proposed by Christoffel, Coenen and Warne (2008).

3 Data Description

We employ data from seven developed economies: US, UK, Euro Area, Germany, France, Italy and Japan. Our target variables are the quarterly change in log real GDP and the quarterly change in seasonally-adjusted log CPI with data sources described in Table B1 in the online appendix. Seasonally-adjusted CPI data is not available for European countries and Japan. As a consequence, we seasonally adjusted data using the X12 filter.

For each country, we build a medium and a large dataset of economic indicators sampled monthly. The datasets are summarized in Table 2 and described in detail in Tables B2 and B3 of the online appendix. When quarterly data are required, we use the average over quarter for factor models, so F-MIDAS nest FADL models[8], and the end of the quarter value for the BVAR as it is popular in the BVAR literature. When possible, we follow the series included in Kuzin et al. (2013) datasets. The medium dataset includes 11-14 variables per country. They are a mix of measures of economic activity, including survey data, prices and financial variables. Similar set of variables have been employed by Carriero et al. (2015). These datasets include oil prices as a common variable.

The number of variables included in the large dataset varies across countries due to data availability as recorded in Table 2. It varies between 57 (Japan, France) and 155 (US). The large dataset includes also all variables in the medium dataset. Because of the international transmission of business cycles shocks, we include some key US variables in the large dataset of the 6 remaining economies, including financial variables such as equity prices and Treasury bond rates. We provide the description of all variables including their datastream code in the Table B3 in the online appendix.[9]

Because of the lack of availability of real-time dataset for the monthly indicators for all our seven countries, we use only data from the currently available vintage as it is generally the case when evaluating forecasts with models for large datasets (as, for example, Smets and Wouters (2007) and Kuzin et al. (2013)).

DSGE models are estimated using quarterly changes in output per capita. They also use inflation measured by the GDP deflator. As consequence, when evaluating forecasts of DSGE models, we change the target variable to growth in output per capita and quarterly GDP deflator inflation. We reestimate forecasting models for these modified target variables for a subset of our reduced-form models to be able to compare predictions of structural and reduced-form models. Table B4 in the online appendix describes the variables employed in the DSGE estimation, including their required

[8]This implies that F-MIDAS specification nests the FADL if the MIDAS weighting function is flat, that is, $\theta_1 = \theta_2 = 1$.

[9]Some variables were seasonally adjusted by the X12 filter before estimation, and they have SA indicated in Table B3.

transformation.

The last observation employed in our forecasting exercise is 2013M9. For US, Japan and UK, we use data from 1975M1 (with exception of UK CPI inflation which is only available from 1980M1), but for other countries, data is only available later as described in Table 2. Data for DSGE estimation is from 1984Q1 for the US, UK and the Euro Area.

4 Evaluation Design

Our first forecast origin is 1993Q1 for US, UK, Japan and France; for Germany and Italy is 1998Q1, and for the Euro Area is 2003Q1. We set the maximum forecast horizon to 8, so we are able to compute measures of forecast accuracy for forecasts up to 2011Q3, that is, we have 75 observations in our out-of-sample period for US, UK, Japan and France; 55 observations for Germany and Italy, and 35 observations for the Euro Area. For some of our results, we split the out-of-sample period in windows of 5 years (20 observations) based on the forecast origin date to verify whether the relative forecasting performance varies over the out-of-sample period. The literature provides evidence that predictive ability may change over time (Giacomini and Rossi, 2010). In addition, changes in the underlying structure of the economy and data characteristics may affect the relative forecasting performance of models.

We compute forecasts from models estimated with expanding samples over the out-of-sample period, that is, at each forecast origin we re-estimate each model and we use all observations available up to the forecasting origin.

We use two measures of forecasting performance. The accuracy of point forecasts is measured by Root Mean Squared Forecast Errors (RMSFE), and the log predictive score measures the accuracy of density forecasts. The advantage of using log scores to compare density forecasts is that the maximization of the logscore is equivalent to minimize the Kullback-Leibler distance between the model and the true density. To compute log scores, we first fit a Gaussian kernel density to the 5000 predictive density draws over a grid between -15 and 15. Then we compute the log score by finding the probability at the outturn.

We use the Diebold and Mariano (1995) t-statistic to test for equal accuracy. The variance is computed with the Newey-West estimator with maximum order increasing with the horizon.

Table 1 provides a short description of all forecasting models we employ in this evaluation. Similarly to Bańbura et al. (2010), we consider BVAR models of three sizes: small, medium and large. We use medium and large datasets for the FADL and MIDAS models, but our only small model is the BVAR. The model has only three variables: real GDP, CPI, and the short-term interest rate.

5 Explaining forecasting performance of statistical models

We provide acronyms for all forecasting models included in this evaluation in Table 1. They comprise 13 reduced-form models, including an univariate model (AR), and one structural model (DSGE). In this section we explore the relative forecasting performance of the 12 multivariate reduced-form models, listed as models 2 to 13 in Table 1. Forecasting comparisons that include the DSGE model are discussed in section 6. We measure the impact of model class, forecasting horizon, dataset size and data source (country) on point and density forecasting performance.

5.1 A Meta Analysis

Our aim is to investigate how the relative (to the AR model) forecasting performance of each statistical model class (MIDAS, FADL and BVAR) varies with the number of predictors (medium vs large dataset), the forecasting horizon (nowcasting, short-horizon ($h = 2, .., 4$) and medium-horizon ($h = 5, ..., 8$), the 5-year subperiod evaluated, and the geographical source of the dataset.

The dependent variable in our meta analysis regression is a measure of the relative forecasting performance of a specific forecasting model to the autoregressive model when predicting one of the target variables (output growth and inflation) for a specific country, horizon and forecasting origin period. The measures of forecasting performance are based on root mean squared forecast errors (RMSFE) and the median logscore (MLS)[10] computed for a specific target variable varying across country, forecasting model, period and horizon. The measures for point and density forecasting performance are:

$$rMSFE_{m,p,c,h} = \frac{RMSFE_{AR,p,c,h}}{RMSFE_{m,p,c,h}};$$

$$rMLS_{m,p,c,h} = 1 + [(-MLS_{ar,p,c,h}) - (-MLS_{m,p,c,h})].$$

where $m = 2, ..., 13$, which are the statistical models numbered 2 up to 13 in Table 1. Each measure varies with the set of forecasting origins employed in the computation p =93Q1-97Q4, 98Q1-02Q4, 03Q1-07Q4, 08Q1-11Q3, 93Q1-11Q3; with the source country c =US, UK, EU, FR, IT, GER, JP, and the forecasting horizon $h = 1, ..., 8$.

As consequence, the total number of relative performance observations (considering that the forecasting period availability varies across countries as noted in Table 2) is 2,976. By exploiting a large set of forecasting comparisons, we aim to find sources of performance improvements in macroeconomic forecasting that are not constrained by model class, forecast horizon, country and evaluation period.

[10] We use the median instead of the mean logscore to minimize the impact of outliers in our analysis. Outlier values are more frequent with logscores than with squared forecast errors.

The first characteristic we explore is the country where data is sourced. We use two dummy variables to split the country set in Table 2 into three: $D^{EU} = 1$ for Euro Area countries (c =EU, FR, IT, GER) (and $D^{EU} = 0$ otherwise), and $D^{JP} = 1$ if c =JP. The benchmark countries are then US and UK.

The second characteristic is the forecasting horizon. We split the set of forecast horizons into three groups by defining $D^{sh} = 1$ if $h = 2, ..., 4$ and $D^{mh} = 1$ if $h = 5, ..., 8$. Accordingly, differences in performance over short and medium horizons are assessed against the nowcasting ($h = 1$) benchmark.

We are also interested in finding differences between the three model classes. We set D^{MIDAS}=1 if $m = 4, 5, 6, 7$ and $D^{BVAR} = 1$ if $m = 8, 9, 10, 11, 12, 13$ based on Table 1 description. The benchmark model class is the FADL ($m = 2, 3$). The impact of the number of predictors is evaluated using $D^{small} = 1$ if $m = 8, 9$ and $D^{l\arg e} = 1$ if $m = 3, 5, 7, 12, 13$, implying that the benchmark dataset size is the medium one.

Finally, the impact of the evaluation period is assessed by creating one dummy variable for each one of the four five-year out-of-sample subperiods. As a consequence, performance improvements are relative to the full out-of-sample (p =93Q1-11Q3).

We also consider interactions between the dummy variables described above. We consider interactions between horizon and model class dummies, between $D^{l\arg e}$ and model class dummies, and between $D^{l\arg e}$ and evaluation period dummies.

The meta-analysis regression is then:

$$\begin{aligned} rLoss_{m,p,c,h} = {} & \beta_0 + \beta_1 D^{JP} + \beta_2 D^{EU} \qquad (3) \\ & + \beta_3 D^{9397} + \beta_4 D^{9802} + \beta_5 D^{0307} + \beta_6 D^{0811} \\ & + \beta_7 D^{sh} + \beta_8 D^{lh} + \beta_9 D^{MIDAS} + \beta_{10} D^{BVAR} \\ & + \beta_{11} D^{MIDAS} * D^{sh} + \beta_{12} D^{MIDAS} * D^{lh} + \beta_{12} D^{BVAR} * D^{sh} + \beta_{14} D^{BVAR} * D^{lh} \\ & + \beta_{15} D^{small} + \beta_{16} D^{l\arg e} + \beta_{17} D^{l\arg e} * D^{BVAR} + \beta_{18} D^{l\arg e} * D^{MIDAS} \\ & + \beta_{19} D^{l\arg e} * D^{9397} + \beta_{20} D^{l\arg e} * D^{9802} + \beta_{21} D^{l\arg e} * D^{0307} + \beta_{22} D^{l\arg e} * D^{0811} + \varepsilon_{m,p,c,h}. \end{aligned}$$

for $m = 2, ..., 13; p =$ 93-97,98-02,03-07,08-11,93-11$; h = 1, ..., 8; c = US, UK, JP, FR, IT, GER, EU$

$rLoss_{m,p,c,h}$ is either $rMSFE_{m,p,c,h}$ or $rMLS_{m,p,c,h}$.

Note that β_0 measures the relative (to the AR model) performance of the the FADL medium model ($m = 2$) for $h = 1$ over the full sample period (p =93-11) with US and UK data ($c = 1, 2$). As consequence, all other coefficient estimates are measures of gains/losses against this benchmark.

5.2 Meta-Analysis Results

Table 3 presents estimates of the regression in (3) with standard errors clustered by country, implying that we consider country-specific effects. The table columns describe results for each performance measure (*rMSFE* and *rMLS)* and target variable (output growth, inflation). Cases where the null hypothesis that the coefficient is equal to zero is rejected are indicated with stars for 10%, 5% and 1% significance levels. Values in bold show estimates are statistically significant at 10% when using heteroscedasticity-robust standard errors instead of the country-clustered standard errors displayed in Table 3.

The characteristics considered in regression (3) explain between 13% and 20% of the forecasting performance depending on the target and the type of performance measure. As a consequence, idiosyncratic variation has an important role in explaining forecasting performance across this large number of forecasting exercises. The following analysis will consider characteristics with statistically significant role in explaining forecasting performance, as indicated in Table 3.

The estimates of the regressions' intercepts are all larger than 1, implying that on average the FADL_M improves over the AR when nowcasting US and UK variables. Gains are larger for output growth and imply a 4% improvement in RMSFE. Estimates for β_1 and β_2 suggest that benefits of employing multivariate models instead of AR models for predicting output growth are larger with Japanese data but smaller with European data.

The estimated coefficients on the evaluation period dummies point to changes in statistical performance over time, but the estimates are statistically significant with country-clustered standard errors only when evaluating output growth point forecasts. During the turbulent 08Q1-11Q3 period, we find that multivariate models perform relatively better for output growth, but they do relatively worse in the 98Q1-11Q3 period.

The estimated coefficients on the forecasting horizon dummies are all negative, implying that the relative performance of multivariate models to the AR model deteriorates with the horizon. This deterioration is statistically significant for point forecasting output growth and inflation when horizon is iterated with the MIDAS model dummy variable. This declining MIDAS forecasting performance with horizon is partially compensated by the fact that MIDAS models improve RMSFEs over the benchmark in 3% on average when nowcasting output growth, albeit the estimate of β_9 is not statistically significant. For predicting output growth, BVAR models do relatively better at medium horizons ($h = 5, ..., 8$) and are significantly better at $h = 2, 3, 4$. These results suggest that although MIDAS models may deliver accurate nowcasts of output growth for some countries, this class of models performance deteriorates rapidly with the forecast horizon and a BVAR specification may be a more accurate choice in some cases.

The estimated coefficients on the dataset-size dummies indicate that BVARs with only three variables, including both targets, are significantly worse than models with a moderate number of indicators in predicting output growth. For predicting inflation, either a small or a medium set of indicators perform significantly better than large datasets.

The interactions between dataset size and model class clearly indicate that large BVAR models deteriorate forecasting performance. These results suggest that if the aim is to exploit information in a large number of predictors (more than 55 indicators) for forecasting output growth and inflation, then the use of models with factors (FADL and F-MIDAS) or forecasting combinations (C-MIDAS) are more adequate than BVAR models. However, there is no evidence that the use of a large number of predictors instead of a dozen picked variables (medium dataset) improves macroeconomic forecasting. By evaluating the estimates for the iterations between $D^{l\arg e}$ and the sample period, we find that a large set of predictors worsens output growth point forecasting performance in the earlier periods when sample sizes employed in the estimation are shorter (recall that we increase sample size when estimating models at each forecasting origin).

In summary, we find some time variation in the relative forecasting performance of multivariate statistical models to AR models for forecasting output growth across countries: multivariate models are in particularly useful during the last four year period (2008-2011). We find no evidence that models with a larger number of predictors improve over the performance of models with smaller set of predictors. If using a large dataset, FADL and MIDAS models are more adequate than BVAR models. We find very limited evidence that MIDAS models improve nowcasts.

5.3 Additional Meta-Analysis Comparisons

For MIDAS and BVAR model classes, we consider two main specification types. For MIDAS models, we compute forecasts by using a factor-augmented version (F-MIDAS) and an equal-weight forecasting combination strategy (C-MIDAS). For BVAR models, we use a specification in levels (L-BVAR) and another in growth rates (D-BVAR). In this subsection, we use relative performance regressions to test if there are any statistical differences in performance between these specification types that hold across countries, horizon, evaluation period and number of predictors.

In Table 4A, we present results for the four measures of performance in Table 3 (output growth and inflation; *rMSFE* and *rMLS*). These are single regressions estimated with performance measures computed only for MIDAS models ($rLoss_{m,p,c,h}$ for $m = 4, ..., 7$ with p, h and c variation as in (3)). We define the dummy variable D^{CMIDAS} as equal to 1 if $m = 6, 7$. As a consequence, if the estimated coefficient of D^{CMIDAS} is significantly positive, we can conclude that the equal-weighted forecasting combination of single regressor MIDAS models is a better way to exploit the information on a set of predictors than using monthly factors. The coefficients are indeed positive and statistically significant with country-clustered standard errors in all columns of Table 4A, so we conclude in favour of the

C-MIDAS specifications.

In Table 4B, we compute single regressions with the same performance measures, but for BVAR models only ($rLoss_{m,p,c,h}$ for $m = 8, ..., 13$ with p, h and c variation as in (3)). We define the dummy variable D^{DBVAR} as equal to 1 if $m = 9, 11, 13$ and zero otherwise. The empirical results can inform us on whether the BVAR-in-differences improves over the BVAR-in-levels. Recall that the main advantage of using the BVAR-in-levels (L-BVAR) is that the possibility of cointegration is allowed for. The results in Table 4B suggest that this BVAR specification choice only matters for point forecasting output growth: L-BVARs perform significantly better than D-BVARs.

5.4 Evaluating the impact of the dataset size with equal accuracy tests

Our previous results suggest that the use of forecasting models with a large set of predictors may have a negative effect on forecasting performance for both output growth and inflation, in particularly if using BVAR models with short samples. In this subsection, we evaluate this research question using the empirical variation of "medium vs large" equal accuracy tests for point and density forecasts as described in section 4.

Figure 1 presents empirical t-statistics distributions for the following models: FADL, F-MIDAS, C-MIDAS, L-BVAR and D-BVAR. The Diebold and Mariano (1995) t-statistics are computed with the specification with a medium dataset under the null and the model with the large dataset under the alternative using the full out-of-sample period (p =93-11). The box plots are computed for t-statistics obtained for different horizons ($h = 1, ..., 8$) and countries. Negative values imply that the model with a large number of predictors is more accurate than the same model with a medium data set. Using a two-sided 5% test, statistical differences are found when the absolute value of the t-stat is larger than 1.96.

In general, the t-statistics are between -1.96 and 1.96, that is, models with large and medium datasets deliver statistically similar point and density forecasting performances. However, based on the median t-statistics, we can say that D-BVARs are worse in handling large datasets than L-BVARs, providing an additional nuance to our results in section 5 discouraging the use of BVARs with large datasets. These results also support the use of the C-MIDAS specification instead of the F-MIDAS in particularly when dealing with large datasets for forecasting inflation.

In summary, there is no strong evidence that a large number of predictors improve forecasts over a moderate ammount, but we can provide evidence to support the use of C-MIDAS and FADL specifications to deal with large datasets instead of BVAR models.

6 Comparing structural vs reduced-form forecasting models

In the previous section, we investigate common features that explain relative forecasting performance of reduced-form statistical models across countries, forecasting horizons, forecasting periods and model specification. In this section, we use equal accuracy tests computed as described in Section 4 to compare the performance of reduced-form statistical models (FADL, BVAR, MIDAS) with the DSGE model.

Details of the DSGE model employed including our estimation strategy were discussed in section 2.4. We describe the dataset employed in the estimation of DSGE models in section 3. One should note that the medium-sized DSGE forecasts are considered only for $c = US, UK, EU$ and they are estimated with output growth per person and GDP deflator inflation. To measure the relative performance of DSGE models to the AR benchmark, we recompute AR forecasts using the same measurements of output growth and inflation employed by the DSGE model.

Figures 2 and 3 present box plots of the Diebold and Mariano (1995) t-statistics. The t-statistics are computed for the full out-of-sample of period for each country as listed in Table 2. Negative values mean that the model is more accurate than the AR model. Using an one-sided test we would reject the null of predictability at 5% if the DM t-statistic is smaller than -1.65. The empirical distributions vary with the country and are computed for a specific model class (FADL, MIDAS, BVAR, DSGE). The box plots are presented separately for three horizons ($h = 1, 4$ and 8). Figure 2 presents results for output growth and inflation using the quadratic loss function (MSFE) to compute the t-statistics. The plots in Figure 3 instead are based on the differences in logscore.

The results in Figures 2 and 3 help us to indicate which model class, including statistical model classes (FADL, MIDAS, BVAR) and the structural model class (DSGE), performs best for each target variable and for a set of forecasting horizons. The median t-statistic in Figures 2 and 3 can be employed to evaluate how each class of model performs on average across specifications and countries for each horizon and target variable.

MIDAS models do better at $h = 1$ for output growth, but the distribution of t-statistics has a large spread, suggesting that mixed frequency models improve output growth nowcasts for the median country but does not perform well for some countries. For $h = 4$, it is clear that BVARs perform better for forecasting output growth. When forecasting inflation, the clear evidence we have is that DSGE models do better when predicting inflation at $h = 4, 8$ for both point and density forecasts. The results in Figures 2 and 3 suggest that DSGE models are able to significantly improve AR forecasts of quarterly inflation at $h = 4, 8$.

These results are supported by detailed Tables by country and forecasting horizon in the online appendix. Table A1 shows the relative performance of the DSGE model against the AR and the FADL_M using RMSFEs and Table A2 shows results with the logscore. They indicate that DSGE gains for forecasting inflation are mainly for the US and the UK, with disappointing results for the Euro area in agreement with Smets, Warne and Wouters (2014). The DSGE model performs better in the earlier period (1993-2002) than in the later period (2003-2011), confirming the literature that supports DSGE forecasts during the Great Moderation period (1985-2007) (Del Negro and Schorftheide, 2013).

In summary, we provide evidence that structural (DSGE) models can deliver superior long horizon forecasts of US and UK inflation.

7 Conclusion

The comprehensive evaluation of macroeconomic forecasting models reported in this paper contributes to the academic literature and the practice of macroeconomic forecasting. By employing datasets for seven developed economies and considering four classes of multivariate forecasting models, we provide new empirical findings, extending and enhancing evidence usually available for US data.

Our multicountry comparison provides a new dimension when comparing structural with reduced-form models in forecasting. The DSGE model specification we consider (Smets and Wouters, 2007) provides accurate one and two-year ahead forecasts of inflation not only for the US but also for the UK.

Our evaluation is designed to look at forecasting horizons from nowcasting up to two-years ahead. Our contribution is to consider a large set of model specifications over all these horizons so we can provide evidence that the choice of the best forecasting model class clearly varies with the forecast horizon. We propose meta-analysis regressions to be able to draw a small set of clear messages from 2,976 relative accuracy comparisons.

We extend results based only on Bayesian VARs (Koop, 2013) by showing that the use of a large set of predictors instead of a moderate set do not improve forecasts. Our contribution is to employ five different specifications from three model classes to address whether it is worth to use large datasets instead of using 10-15 chosen predictors for both point and density forecasting, and we find that indeed a medium dataset typically suffices. When dealing with a large number of predictors (more than 50) to estimate a forecasting model over a short time period, we find that factor augmented distributed lag models and equal-weighted combinations of single-predictor mixed-data sampling regressions perform better than BVARs in predicting key macroeconomic variables when considering point and density forecasting.

References

Aastveit, K. A., Foroni, C. and Ravazzolo, F. (2016). Density forecasts with MIDAS models, *Journal of Applied Econometrics* **32**: 783–801.

Andreou, E., Ghysels, E. and Kourtellos, A. (2013). Should macroeconomic forecasters look at daily financiaoutput and how?, *Journal of Business and Economic Statistics* **31**: 240–251.

Banbura, M., Giannone, D., Modugno, M. and Reichlin, L. (2013). Now-casting and the real-time data flow, *Handbook of Economic Forecasting, volume 2A*, Elsevier, chapter 4, pp. 195–237.

Bańbura, M., Giannone, D. and Reichlin, L. (2010). Large bayesian vector autoregressions, *Journal of Applied Econometrics* **25**(1): 71–92.

Carriero, A., Clark, T. E. and Marcellino, M. (2015). Bayesian VARs: Specifications choices and forecast accuracy, *Journal of Applied Econometrics* **30**: 46–73.

Chauvet, M. (1998). An econometric characterization of business cycle dynamcis with factor structure and regime switches., *International Economic Review* **39**: 969–96.

Chauvet, M. and Potter, S. (2013). Forecasting output, *Handbook of Economic Forecasting, volume 2A*, Elsevier, chapter 3, pp. 141–194.

Christoffel, K., Coenen, G. and Warne, A. (2008). The new area-wide model of the euro area: a micro-founded open-economy model for forecasting and policy analysis, *ECB Working Paper Series n. 944* .

Christoffel, K., Coenen, G. and Warne, A. (2010). Forecasting with DSGE models, *ECB Working Paper Series n. 1185* .

Clark, T. E. (2011). Real-time density forecasts from baryesian vector autoregressions with stochastic volatility, *Journal of Business and Economic Statistics* **29**.

Clements, M. P. and Galvão, A. B. (2008). Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the United States, *Journal of Business and Economic Statistics* **26**: 546–554. No. 4.

Clements, M. P. and Taylor, N. (2001). Bootstrapping prediction intervals for autoregressive models, *International Journal of Forecasting* **17**: 247–267.

D'Agostino, A., Gambetti, L. and Giannone, D. (2013). Macroeconomic forecasting and structural change, *Journal of Applied Econometrics* **28**: 82–101.

Del Negro, M. and Schorftheide, F. (2011). Bayesian macroeconometrics, *The Oxford Handbook of Bayesian Econometrics* pp. 293–389.

Del Negro, M. and Schorftheide, F. (2013). DSGE model-based forecasting, *Handbook of Economic Forecasting, volume 2A*, Elsevier, chapter 2, pp. 57–140.

Diebold, F. X. and Mariano, R. S. (1995). Comparing predictive accuracy, *Journal of Business and Economic Statistics* **13**: 253–263. Reprinted in Mills, T. C. (ed.) (1999), *Economic Forecasting. The International Library of Critical Writings in Economics.* Cheltenham: Edward Elgar.

Diebold, F. X., Schorftheide, F. and Shin, M. (2017). Real-time forecast evaluation of DSGE models with stochastic volatility, *Journal of Econometrics* **(in press)**.

Edge, R. M. and Gurkaynak, R. S. (2011). How useful are estimated DSGE model forecasts, *Federal Reserve Board, Finance and Economics Discussion Series* **11**.

Faust, J. and Wright, J. H. (2013). Forecasting inflation, *Handbook of Economic Forecasting, volume 2A*, Elsevier, chapter 1, pp. 3–56.

Ferrara, L., Marcellino, M. and Mogliani, M. (2015). Macroeconomic forecasting during the Great Recession: the return of non-linearity?, *International Journal of Forecating* **31**: 664–679.

Giacomini, R. and Rossi, B. (2010). Forecast comparisons in unstable environments, *Journal of Applied Econometrics* **25**: 595–620.

Giannone, D., Lenza, M. and Primiceri, G. E. (2015). Prior selection for vector autoregressions, *Review of Economic and Statistics* **97**: 412–435.

Groen, J. J. J. and Kapetanios, G. (2013). Model selection criteria for factor-augmented regressions, *Oxford Bullettin of Economics and Statistics* **75**: 37–63.

Herbst, E. and Schorftheide, F. (2012). Evaluating DSGE model forecasts of comovements, *Journal of Econometrics* **171**: 152–166.

Koop, G. (2013). Forecasting with medium and large Bayesian VARs, *Journal of applied econometrics* **28**: 177–203.

Koop, G. and Korobilis, D. (2013). Large time-varying parameter vars, *Journal of Econometrics* **177**: 185–198.

Kuzin, V., Marcellino, M. and Schumacher, C. (2013). Pooling versus model selection for nowcasting with many predictors: Empirical evidence for six industrialized countries, *Journal of Applied Econometrics* **28**: 392–411.

Schorfheide, F. and Song, D. (2015). Real-time forecasting with a mixed-frequency VAR, *Journal of Business and Economic Statistics* **33**: 366–380.

Sims, C. (1993). A nine-variable probabilistic macroeconomic forecasting model, *Business Cycles, Indicators and Forecasting*, National Bureau of Economic Research, pp. 179–212.

Sims, C. (2000). Using a likelihood perspective to sharpen econometric discourse: three examples., *Journal of Econometrics* **95**(2): 443–462.

Smets, F., Warne, A. and Wouters, R. (2014). Professional forecasters and real-time forecasting with a dsge model, *International Journal of Forecasting* **30**: 981–995.

Smets, F. and Wouters, R. (2007). Shocks and frictions in US business cycles., *American Economic Review* **97**: 586–606.

Stock, J. H. and Watson, M. W. (2002). Macroeconomic forecasting using diffusion indexes, *Journal of Business and Economic Statistics* **20**: 147–162.

Stock, J. H. and Watson, M. W. (2003). Forecasting output and inflation: The role of asset prices, *Journal of Economic Literature* **41**: 788–829.

Stock, J. H. and Watson, M. W. (2007). Why has U.S. Inflation Become Harder to Forecast?, *Journal of Money, Credit and Banking* **Supplement to Vol. 39**: 3–33.

Woulters, M. H. (2015). Evaluating point and density forecasts of DSGE models, *Journal of Applied Econometrics* **30**: 74–96.

Table 1: Model Acronyms

m	Name	Description
1	AR	Autoregressive Model
2	FADL_M	Factor ADL model with medium-sized dataset
3	FADL_L	Factor ADL model with large-sized dataset
4	F-MIDAS_M	Factor MIDAS with medium-sized dataset
5	F-MIDAS_L	Factor MIDAS with large-sized dataset
6	C-MIDAS_M	Combination MIDAS with medium-sized dataset
7	C-MIDAS_L	Combination MIDAS with large-sized dataset
8	L-BVAR_S	BVAR in levels with small dataset.
9	D-BVAR_S	BVAR in differences with small dataset.
10	L-BVAR_M	BVAR in levels with medium-sized dataset.
11	D-BVAR_M	BVAR in differences with medium-sized dataset.
12	L-BVAR_L	BVAR in levels with large-sized dataset.
13	D-BVAR_L	BVAR in differences with large-sized dataset.
14	DSGE	Smets and Wouters (2007) medium-sized DSGE model.

Table 2: Data Summary

	Country	Sample Period	Out-of-sample period	Medium Dataset – number of predictors	Large Dataset – number of predictors
1	US	1975M1-2013M9	1993Q1-2013Q3	14	155
2	UK	1975M1-2013M9	1993Q1-2013Q3	13	59
3	Japan	1975M1-2013M9	1993Q1-2013Q3	13	57
4	France	1983M1-2013M9	1993Q1-2013Q3	13	57
5	Italy	1990M1-2013M9	1998Q1-2013Q3	12	128
6	Germany	1991M1-2013M9	1998Q1-2013Q3	13	114
7	Euro area	1998M4-2013M9	2003Q1-2013Q3	11	81

Note: Full description of time series employed, data sources and data transformations are available in the online data appendix. Table B1 describes the target variables, Table B2 describes the monthly medium-sized datasets, Table B3 the monthly large datasets and Table B4 has the description and transformations of the series employed to estimate the DSGE models.

Table 3: Explaining Relative Forecasting Performance by country, forecasting origin period, horizon, model class and dataset size.

	rMSFE		rMLS	
	Output Growth	Inflation	Output Growth	Inflation
const (FADL_M, h=1 93-11, US+UK)	**1.037***** 0.026)	**1.017***** (0.015)	**1.041***** (0.042)	**1.057***** (0.054)
Japan	**0.016***	**0.068*****	0.011	**-0.022**
	(0.009)	(0.004)	(0.028)	(0.057)
Euro Area (Euro, GER, IT, FR)	**-0.038***	-0.012	-**0.100**	**-0.066**
	(0.015)	(0.028)	(0.064)	(0.068)
93Q1-97Q4	**-0.068**	**0.077**	-0.001	**0.068**
	(0.043)	(0.047)	(0.025)	(0.044)
98Q1-02Q4	**-0.037*****	**0.022**	**0.022**	-0.016
	(0.008)	(0.036)	(0.031)	(0.027)
03Q1-07Q4	0.003	0.006	0.001	-0.005
	(0.009)	(0.032)	(0.024)	(0.046)
08Q1-11Q3	**0.039****	0.013	**0.068**	-0.008
	(0.020)	(0.025)	(0.056)	(0.039)
h=2,…,4	**-0.040***	-0.012	-0.002	-0.028
	(0.023)	(0.025)	(0.030)	(0.019)
h=5,..,8	**-0.028**	**-0.035**	**-0.065**	**-0.057***
	(0.028)	(0.039)	(0.063)	(0.035)
MIDAS (h=1)	0.029	-0.002	0.011	0.012
	(0.029)	(0.039)	(0.025)	(0.047)
BVAR (h=1)	-0.013	-0.011	0.004	**-0.098***
	(0.017)	(0.031)	(0.039)	(0.057)
(h=2,…,4)*MIDAS	-0.021	-0.033	-0.035**	-**0.051**
	(0.027)	(0.032)	(0.018)	(0.043)
(h=5,…,8)*MIDAS	**-0.060****	-0.006	-0.048**	-0.024
	(0.026)	(0.025)	(0.021)	(0.049)
(h=2,…,4)*BVAR	**0.058*****	-0.013	-0.025	-0.007
	(0.020)	(0.026)	(0.024)	(0.037)
(h=5,…,8)*BVAR	0.024	0.006	-0.019	0.028
	(0.026)	(0.028)	(0.057)	(0.055)
Small	-**0.031***	**0.027**	-0.005	0.002
	(0.019)	(0.025)	(0.015)	(0.034)
Large	-0.003	**-0.048*****	-0.011	-0.019
	(-0.003)	(0.018)	(0.007)	(0.016)
Large* BVAR	**-0.029***	-**0.070***	**-0.163*****	-**0.201*****
	(0.017)	(0.042)	(0.055)	(0.041)
Large*MIDAS	0.001	0.021	-0.013	-0.030*
	(0.014)	(0.023)	(0.026)	(0.018)
Large*(93-97)	**-0.031**	**0.127**	**0.037**	**0.121*****
	(0.024)	(0.081)	(0.038)	(0.041)
Large*(98-02)	**-0.021****	**-0.062**	0.007	-0.040
	(0.010)	(0.048)	(0.024)	(0.027)
Large*(03-07)	-0.002	0.012	-0.010	-0.021
	(0.007)	(0.014)	(0.015)	(0.015)

Large*(07-11)	0.008 (0.014)	-0.003 (0.021)	0.009 (0.022)	0.001 (0.026)
R^2	0.154	0.126	0.156	0.198
n. obs.	2976	2976	2976	2976
Mean of dep. var.	0.978	0.986	0.929	0.888

Note: Values larger than 1 imply that model improves over the AR. All explanatory variables are dummy variables. Regressions estimated by OLS. Values in brackets are standard errors clustered by country. *,**,*** denote rejection of the null of no statistical accuracy, respectively, at 10%, 5% and 1%. Values in bold denote the estimates that are statistical significant at 10% if we use a heteroscedasticity-consistent (White) standard errors.

Table 4: Additional Regressions

Table 4A: C-MIDAS vs F-MIDAS with observations for only MIDAS specifications

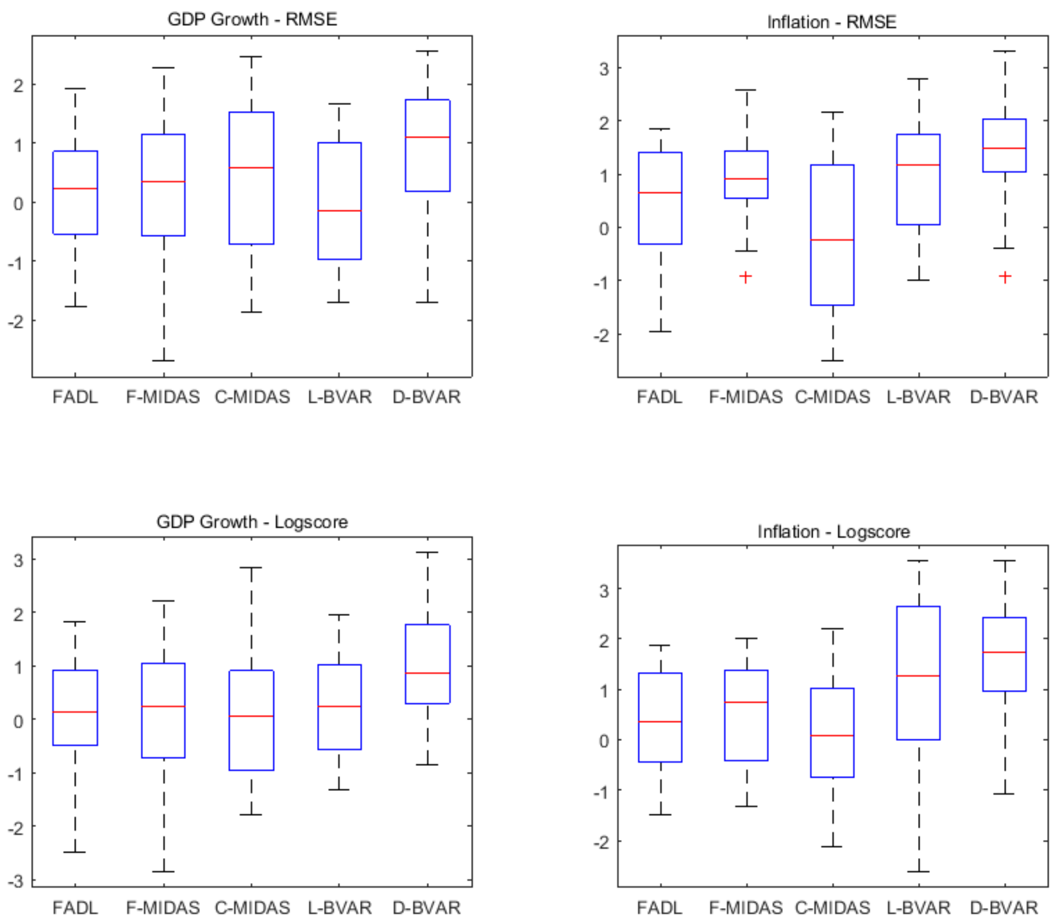
	rMSFE		rMLS	
	Output Growth	Inflation	Output Growth	Inflation
C-MIDAS	**0.048***** (0.006)	**0.078**** (0.034)	**0.041***** (0.011)	**0.129***** (0.028)
R^2	0.031	0.037	0.006	0.048
n. obs.	992	992	992	992
Mean of dep. var.	0.971	0.991	0.941	0.940

Table 4B: D-BVAR vs L-BVAR with observations for only BVAR specifications

	rMSFE		rMLS	
	Output Growth	Inflation	Output Growth	Inflation
D-BVAR	**-0.037*** (0.021)	-**0.050** (0.056)	-0.008 (0.070)	**0.069** (0.093)
R^2	0.022	0.015	0.001	0.020
n. obs.	1488	1488	1488	1488
Mean of dep. var.	0.981	0.977	0.904	0.824

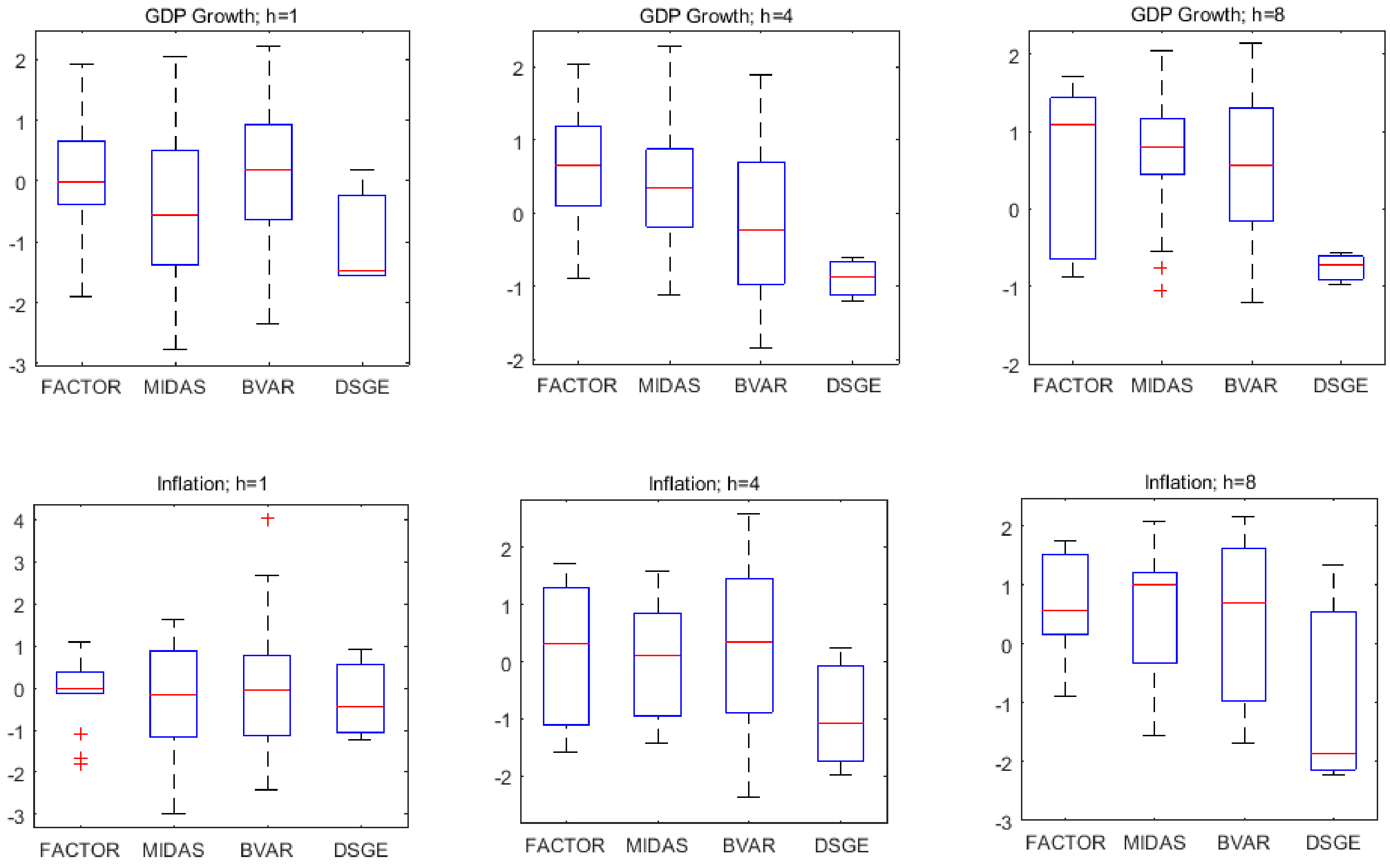
Note: Regressions estimated by OLS. Values in brackets are standard errors clustered by country. *,**,*** denote rejection of the null of no statistical accuracy, respectively, at 10%, 5% and 1%. Values in bold denote the estimates that are statistical significant at 10% if we use a heteroscedasticity-consistent (White) standard errors.

Figure 1: Box plots of the equal accuracy t-statistic for a model with a medium dataset against a large dataset for each indicated forecasting model (aggregate over forecasting horizons (1 to 8) and countries; full out-of-sample period).



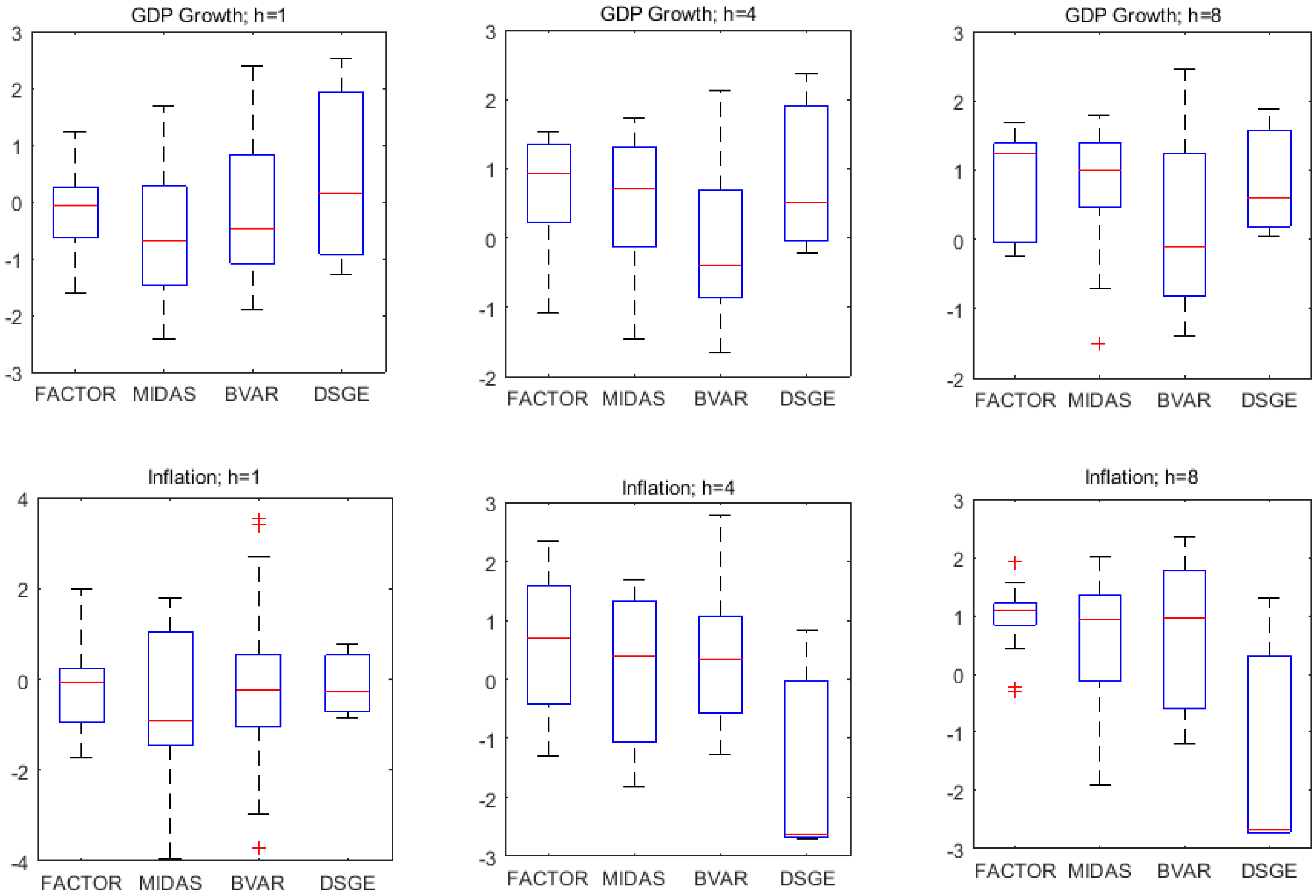
Note: Negative t-statistics imply that the specification with large dataset is more accurate than the equivalent with medium-sized dataset. Each box plot is based on 8 horizons x 7 countries= 56 values. See notes of Figure 1. In the first panel, the accuracy test is based on MSFEs, and in the second panel, the statistics are based on the logscore.

Figure 2: Box plots of the equal accuracy MSFE t-statistics with the AR model under the null and a forecasting model from the model class indicated under the alternative (aggregate over specifications and countries; full out-of-sample period).



Note: First panel has results for forecasting GDP growth for horizons 1, 4 and 8. The second panel has equivalent results for forecasting inflation. See Table 1 for the description of Factor (2-3), MIDAS (4-7) and BVAR (8-13) specifications. Note that the DSGE is estimated only for 3 countries. List of the 7 countries employed are in Table 2. Negative values are in favour of the specified multivariate model class. "On each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considered outliers, and outliers are plotted individually." (Matlab description).

Figure 3: Box plots of the equal accuracy Logscore t-statistics with the AR model under the null and a forecasting model from the model class indicated under the alternative (aggregate over specifications and countries; full out-of-sample period).



Note: See notes of Figure 1.

Online Data Appendix for “A comprehensive evaluation of macroeconomic forecasting methods” by A. Carriero, A. Galvao and G. Kapetanios. October 2017.

Table A1: Comparison between DSGE and Statistical Models using RMSFEs

Table A1A: Forecasting Output Growth per person

		1993Q1-1997Q4				1998Q1-2002Q4				2003Q1-2007Q4				2008Q1-2011Q3				All Periods			
		h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
US	AR	0.39	0.37	0.40	0.43	0.60	0.58	0.61	0.58	0.47	0.49	0.84	1.00	0.87	1.01	0.68	0.38	0.59	0.63	0.65	0.66
	FADL_M	0.41	0.39	0.43	0.52	0.61	0.57	0.62	0.57	0.48	0.49	0.83	1.00	0.85	0.97	0.68	0.49	0.59	0.62	0.65	0.69
	DSGE/AR	0.99	0.97	1.08	1.27	0.76**	0.89	0.89	0.96	0.94	0.92	0.80	0.80	0.88	0.88	0.92	1.17	0.87*	0.90*	0.88	0.93
	DSGE/FADL_M	0.95	0.92	1.01	1.05	0.76**	0.91	0.88	0.97	0.93	0.91	0.81	0.80	0.90	0.91	0.93	0.92	0.87*	0.91*	0.88*	0.89
UK	AR	0.43	0.41	0.43	0.46	0.49	0.50	0.49	0.41	0.52	0.62	1.00	1.24	1.10	1.12	1.00	0.45	0.65	0.68	0.76	0.74
	FADL_M	0.41	0.41	0.43	0.41	0.58	0.55	0.54	0.44	0.56	0.67	1.06	1.30	1.15	1.19	0.99	0.49	0.69	0.73	0.79	0.77
	DSGE/AR	0.86	0.71*	0.81	1.02	0.88	0.80**	1.08	1.07	0.92	0.86	0.85	0.89	0.93	1.10	1.05	1.26	0.91*	0.98	0.95	0.95
	DSGE/FADL_M	0.89	0.72*	0.82	1.14	0.74**	0.73**	0.98	1.00	0.86	0.80	0.80	0.85	0.89	1.03	1.06	1.17	0.86**	0.92	0.91	0.92
Eurozone	AR	-	-	-	-	-	-	-	-	0.26	0.32	0.31	0.99	1.22	1.78	2.28	3.55	0.77	1.12	1.42	2.31
	FADL_M	-	-	-	-	-	-	-	-	0.25	0.31	0.40	1.66	1.16	1.62	1.32	0.75	0.74	1.02	0.87	1.39
	DSGE/AR	-	-	-	-	-	-	-	-	1.26	1.10	2.05	1.03	1.07	0.73	0.52	0.25	1.09	0.76	0.62	0.42
	DSGE/FADL_M	-	-	-	-	-	-	-	-	1.33	1.16	1.57	0.61	1.12	0.81	0.89	1.16	1.14	0.83	1.01	0.69

Table A1B: Forecasting GDP Deflator Inflation

		1993Q1-1997Q4				1998Q1-2002Q4				2003Q1-2007Q4				2008Q1-2011Q3				All Periods			
		h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
US	AR	0.14	0.19	0.25	0.36	0.14	0.17	0.19	0.24	0.25	0.24	0.25	0.38	0.25	0.29	0.34	0.26	0.20	0.22	0.26	0.32
	FADL_M	0.11	0.11	0.11	0.18	0.15	0.19	0.23	0.38	0.26	0.25	0.32	0.47	0.23	0.28	0.34	0.35	0.19	0.22	0.26	0.36
	DSGE/AR	0.88**	0.87*	0.79**	0.85*	1.07	1.04	0.89	0.82	1.02	1.07	0.97	0.77	0.90	0.94	0.96	0.79	0.97	0.98	0.91	0.81**
	DSGE/FADL_M	1.17	1.49	1.86	1.71	0.98	0.91	0.74*	0.51*	0.98	1.00	0.74**	0.62	0.98	0.95	0.96	0.59	1.00	1.01	0.90	0.71*
UK	AR	0.83	0.80	0.96	1.08	0.77	0.79	0.75	0.72	0.54	0.54	0.54	0.58	0.91	0.91	0.78	0.86	0.77	0.76	0.77	0.83
	FADL_M	0.78	0.73	0.87	1.15	0.74	0.75	0.70	0.57	0.53	0.53	0.49	0.66	0.87	0.86	0.70	0.87	0.73	0.72	0.70	0.84
	DSGE/AR	0.82	0.81	0.65*	0.60*	1.08	1.01	0.95	0.84*	0.91**	0.93	0.87*	0.82*	0.86**	0.82*	0.95	0.88	0.92	0.89*	0.83**	0.75**
	DSGE/FADL_M	0.87	0.89	0.72*	0.56*	1.12	1.06	1.02	1.07	0.93	0.94*	0.96	0.72*	0.90	0.87**	1.05	0.86	0.96	0.94	0.91	0.74**
Eurozone	AR	-	-	-	-	-	-	-	-	0.16	0.16	0.17	0.17	0.21	0.20	0.27	0.28	0.18	0.17	0.21	0.22
	FADL_M	-	-	-	-	-	-	-	-	0.18	0.18	0.16	0.54	0.17	0.13	0.24	0.30	0.18	0.16	0.20	0.46
	DSGE/AR	-	-	-	-	-	-	-	-	1.44	1.30	1.25	1.84	0.96	1.00	0.90	0.96	1.22	1.17	1.05	1.37
	DSGE/FADL_M	-	-	-	-	-	-	-	-	1.28	1.14	1.27	0.60	1.21	1.52	1.00	0.89	1.26	1.24	1.13	0.65

Note: For each country, the first panel presents RMSFEs and the second panel presents ratios to AR and FADL_M. *,**,*** denote rejection of the null of equal forecasting accuracy (DM test) in favour of the DSGE model, respectively, at 10%, 5% and 1%.

Table A2: Comparison between DSGE and Statistical Models using Logscores

Table A2A: Forecasting Output Growth per Person

		1993Q1-1997Q4				1998Q1-2002Q4				2003Q1-2007Q4				2008Q1-2011Q3				All Periods			
		h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
US	AR	-0.73	-0.75	-0.77	-0.79	-1.02	-0.96	-1	-0.97	-0.81	-0.81	-1.09	-1.31	-1.2	-1.24	-0.96	-0.71	-0.92	-0.92	-0.96	-0.96
	FADL_M	-0.73	-0.72	-0.76	-0.84	-1.02	-0.96	-1.06	-0.97	-0.81	-0.8	-0.99	-1.41	-1.16	-1.13	-1	-0.78	-0.91	-0.89	-0.95	-1.02
	DSGE/AR	-0.04	-0.05	-0.11	-0.18	0.24**	0.09	0.09	0.04	0.07	0.02	-0.01	0.12	0.04	-0.11	-0.1	-0.14	0.08	-0.01	-0.03	-0.04
	DSGE/FADL_M	-0.04	-0.08	-0.12	-0.13	0.23**	0.08	0.15	0.03	0.07	0.01	-0.1	0.23	0	-0.21	-0.06	-0.07	0.07	-0.04	-0.03	0.02
UK	AR	-0.77	-0.76	-0.82	-0.89	-0.86	-0.88	-0.88	-0.79	-0.92	-1	-1.26	-1.59	-1.44	-1.68	-1.35	-0.85	-0.97	-1.04	-1.06	-1.04
	FADL_M	-0.79	-0.77	-0.85	-0.83	-1.01	-0.98	-0.98	-0.98	-0.97	-1.09	-1.5	-1.71	-1.57	-1.52	-1.27	-1	-1.05	-1.06	-1.14	-1.14
	DSGE/AR	-0.31	-0.35	-0.32	-0.32	-0.13	-0.13	-0.21	-0.26	-0.04	-0.02	-0.03	0.06	-0.06	-0.06	-0.12	-0.23	-0.14	-0.14	-0.17	-0.18
	DSGE/FADL_M	-0.29	-0.34	-0.29	-0.38	0.02	-0.03	-0.1	-0.07	0.01	0.07	0.21	0.19	0.07	-0.22	-0.2	-0.08	-0.06	-0.12	-0.09	-0.09
Eurozone	AR	-	-	-	-	-	-	-	-	-0.14	-0.31	-0.3	-2.17	-3.54	-4.15	-4.31	-1.13	-1.42	-1.75	-1.8	-1.78
	FADL_M	-	-	-	-	-	-	-	-	-0.01	-0.17	-1.73	-2.97	-4.3	-5.71	-4.08	-0.73	-1.62	-2.25	-2.61	-2.13
	DSGE/AR	-	-	-	-	-	-	-	-	-0.31	-0.18	-0.84	-0.05	0.13	0.64	2.04	-0.01	-0.14	0.13	0.24	-0.04
	DSGE/FADL_M	-	-	-	-	-	-	-	-	-0.44	-0.32	0.59	0.76	0.88	2.2	1.81	-0.41	0.06	0.62	1.05	0.32

Table A2B: Forecasting GDP Deflator Inflation

		1993Q1-1997Q4				1998Q1-2002Q4				2003Q1-2007Q4				2008Q1-2011Q3				All Periods			
		h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
US	AR	0.37	0.16	-0.13	-0.44	0.37	0.18	-0.02	-0.25	-0.04	-0.04	-0.1	-0.49	-0.1	-0.24	-0.39	-0.21	0.17	0.03	-0.15	-0.36
	FADL_M	0.39	0.36	0.3	0.01	0.35	0.14	-0.07	-0.67	-0.09	-0.07	-0.37	-0.83	-0.03	-0.3	-0.42	-0.49	0.17	0.06	-0.12	-0.5
	DSGE/AR	0.15***	0.08*	0.18**	0.19**	0.07	0.07*	0.25**	0.35*	-0.11	-0.06	0.09	0.30*	0.16	0.09	0.06	0.25*	0.06	0.04	0.15***	0.28***
	DSGE/FADL_M	0.13*	-0.11	-0.26	-0.26	0.1	0.11	0.30**	0.77*	-0.06	-0.03	0.36**	0.65	0.1	0.15**	0.1	0.54*	0.07	0.02	0.12*	0.42**
UK	AR	-1.21	-1.18	-1.33	-1.45	-1.14	-1.17	-1.17	-1.2	-0.92	-0.93	-1	-1.07	-1.51	-1.49	-1.19	-1.28	-1.17	-1.17	-1.17	-1.25
	FADL_M	-1.17	-1.14	-1.25	-1.7	-1.11	-1.15	-1.12	-1.02	-0.9	-0.94	-0.91	-1.07	-1.32	-1.27	-1.13	-1.44	-1.11	-1.11	-1.1	-1.3
	DSGE/AR	0.14	0.12	0.35**	0.44*	-0.21	-0.08	0.08	0.20*	0.07	0.13**	0.21**	0.22*	0.16	0.31	0.06	0.14	0.03	0.11	0.18***	0.26***
	DSGE/FADL_M	0.1	0.09	0.28*	0.69*	-0.25	-0.1	0.03	0.02	0.05	0.14**	0.11**	0.23*	-0.03	0.08	0	0.3	-0.03	0.05	0.11**	0.31**
Eurozone	AR	-	-	-	-	-	-	-	-	0.35	0.31	0.37	0.28	-0.02	0.06	-0.73	-0.81	0.21	0.22	-0.04	-0.13
	FADL_M	-	-	-	-	-	-	-	-	0.14	0.07	0.36	-0.73	0.43	0.56	-0.44	-1.22	0.25	0.26	0.06	-0.91
	DSGE/AR	-	-	-	-	-	-	-	-	-0.29	-0.38	-0.64	-0.83	0.08	-0.22	0.31	0.16	-0.15	-0.32	-0.28	-0.46
	DSGE/FADL_M	-	-	-	-	-	-	-	-	-0.09	-0.15	-0.63	0.17	-0.37	-0.72	0.03	0.57	-0.2	-0.36	-0.38	0.32

Note: For each country, the first panel presents logscores and the second panel presents differences to AR and FADL_M. *,**,*** denote rejection of the null of equal forecasting accuracy (DM test) in favour of the DSGE model, respectively, at 10%, 5% and 1%.

Table B1: Dependent Variables

	UK
Prices	CPI: Consumer Price Index Consumer Price Indices Cost of Living IDX Inflation, UKXCPI..F, Source: Oxford Economics
Output	GDP: British Pound Sterling Chained DOM GDP GRS MKT Mrkt PRC PRD TOT, UKGDP...D, Source: ONS
	US
Prices	CPI: Consumer price index, AR, SA, Index, 2005=100, USOCFCPIE, Source: OECD Economic Outlook, Copyright OECD
Output	GDP: National Product Account, Gross Domestic Product, Overall, Total, Constant Prices, AR, SA, USD, 2009 chnd prices, USGDP...D; Spurce: U.S. Bureau of Economic Analysis (BEA)
	Euro Zone
Prices	Harmonised Index of Consumer Prices - (Index), CP00, Consumer Price Index (DS Calculated Before 1990, Harmonised), Index, 2005 = 100, Source: Eurostat
Output	GDP - Euro Zone, GDP, real, Constant Prices, SA, EUR, 2005 prices; Source Oxford Economics, EKXGDPR.D
	Japan
Prices	CPI: Consumer Price Index Consumer Price Indices Cost of Living IDX Inflation NATL Ncl Ntl; JPCONPRCF; Source: Thomson Reuters/Statistics Bureau, MIC, Japan
Output	GDP: Chained DOM GDP GRS Japanese Yen PRC PRD Spending TOT; JPGDP...D; Source: Cabinet Office, Japan
	Germany
Prices	CPI: Germany, Consumer Prices, All Items, Total, Index, 2010=100; BDCONPRCF; Source: Federal Statistical Office, Germany
Output	GDP: Germany, Expenditure Approach, Gross Domestic Product, Total, Constant Prices, Cal Adj, SA, EUR, 2010 prices; BDGDP...D; Source: Federal Statistical Office, Germany
	France
Prices	CPI: France, Consumer Prices, All items, Linked and Rebased, Index, 1998=100; FRCONPRAF; INSEE/Thomson Reuters
Output	GDP: France, Expenditure Approach, Gross Domestic Product, Total, Constant Prices, Cal Adj, SA, EUR, 2005 prices; FRGDP...D; Source: INSEE
	Italy
Prices	CPI: Italy, Consumer Prices, By Commodity, All Items, Total, Index, 2010=100; ITCONPRCF; Source: National Institute of Statistics (Istat), Italy
Output	GDP: Italy, Production Approach, Gross Domestic Product, Total, Constant Prices, Cal Adj, SA, EUR, 2005 chnd prices; ITGDP...D; National Institute of Statistics (Istat), Italy

Table B2: Medium-sized datasets

	Variable Name	Log vs Level	Transformation	Datastream code
	US			
1	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA	1	2	USIPTOT.G
2	US CAPACITY UTILIZATION RATE - ALL INDUSTRY SADJ	0	1	USCAPUTLQ
3	US UNEMPLOYMENT RATE SADJ	0	2	USUN%TOTQ
4	US EMPLOYED - NONFARM INDUSTRIES TOTAL (PAYROLL SURVEY) VOLA	1	1	USEMPALLO
5	US PERSONAL CONSUMPTION EXPENDITURES (AR) CURA	1	1	USPERCONB
6	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA	1	2	USHOUSE.O
7	S&P 500 COMPOSITE - PRICE INDEX	1	2	S&PCOMP
8	US US $ NOMINAL EFFECTIVE EXCHANGE RATE	1	2	USE$EF..
9	US FEDERAL FUNDS RATE (MONTHLY AVERAGE)	0	1	USFDFUND
10	US TREASURY YIELD 10 YEAR MINUS US TREASURY BILL RATE - 3 MONTH (EP)	0	1	USTRCN10 - USGBILL3
11	US PPI - FINISHED GOODS SADJ	1	1	USPROPRCE
12	US UMICH CSS: CONSUMER SENTIMENT - EXPECTATIONS VOLN	1	1	USUMCONEH
13	US CHAIN-TYPE PRICE INDEX FOR PERSONAL CONSMPTN.EXPENDITURE SADJ	1	1	USCP...CE
14	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
	UK			
1	UK INDEX OF PRODUCTION - ALL PRODUCTION INDUSTRIES VOLA	1	2	UKIPTOT.G
2	UK LFS: IN EMP.: AGED 16+: ANNUAL = SPRING QUARTER(MAR-MAY) VOLA	1	2	UKMGRZ..O
3	UK UNEMPLOYMENT RATE SADJ	0	2	UKUN%TOTQ
4	UK GFK CONSUMER CONFIDENCE INDEX NADJ	0	1	UKGFKCCNR
5	UK LSL/ ACAD AVERAGE HOUSE PRICE CURA	1	2	UKFTHPI.B
6	UK FT ALL SHARE INDEX (EP) NADJ	1	2	UKSHRPRCF
7	UK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	UKOCC011
8	UK INTERBANK RATE - 3 MONTH (MONTH AVG)	0	1	UKINTER3
9	UK PPI - OUTPUT OF MANUFACTURED PRODUCTS (HOME SALES) NADJ	1	1	UKPROPRCF
10	UK BANK OF ENGLAND BASE RATE (EP)	0	1	UKPRATE.
11	UK YIELD 10-YEAR MINUS UK DISCOUNT RATE 3-MONTH TREASURY BILLS	0	1	UKOIR080R - UKOIR077R
12	UK RPI - ALL ITEMS EXCLUDING MORTGAGE INTEREST NADJ	1	1	UKRPAXMIF
13	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
	EUROZONE			
1	EK INDUSTRIAL PRODUCTION: MANUFACTURING (EA18) VOLA	1	2	EKIPMAN.G
2	EK UNEMPLOYMENT (EA18) VOLA	1	2	EKESTUNPO
3	EK INDUSTRIAL PRODN. - CONSUMER NON DURABLES (%MOM) (EA18) SADJ	0	1	EKESICN%Q
4	EK NEW RESIDENTIAL BUILDINGS - COST INDEX (EA18) NADJ	1	2	EKECEIBCF
5	EURO STOXX - PRICE INDEX	1	2	DJEURST
6	BD DISCOUNT RATE / SHORT TERM EURO REPO RATE	0	2	BDPRATE.
7	EK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	EKOCC011
8	EK ECONOMIC SENTIMENT INDICATOR (EA18) VOLA	1	1	EKEUSESIG
9	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
10	EK CONSTRUCTION SURVEY: EMPLOYMENT EXPECTATIONS (EA) SADJ	0	2	EK45.4BSQ
11	SPREAD GERMANY: BD LONG TERM GOVERNMENT BOND YIELD 9-10 YEARS MINUS BD 3-MONTH FIBOR	0	1	BDGBOND. - BDOIR076R
	GERMANY			
1	BD INDUSTRIAL PRODUCTION INCLUDING CONSTRUCTION (CAL ADJ) VOLA	1	1	BDIPTOT.G
2	BD CNSTR.IND.: CAPACITY UTILIZATION SADJ	0	2	BDIFDCTNQ
3	BD UNEMPLOYMENT RATE, TOTAL SADJ	0	2	BDESUNEMO
4	BD EMPLOYMENT DURATION - SHORT-TERM WORKERS VOLN	1	1	BDEMPSTWP
5	BD NEW ORDERS TO MANUFACTURING - DOMESTIC: CONSUMER GOODS VOLA	1	1	BDDCNORDG
6	BD DAX SHARE PRICE INDEX, EP NADJ	1	2	BDSHRPRCF
7	BD REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	BDOCC011
8	BD CONSTRUCTION ORDERS RECEIVED - RESIDENTIAL CONSTRUCTION VOLA	1	2	BDHOUSE.G
9	BD DISCOUNT RATE / SHORT TERM EURO REPO RATE	0	2	BDPRATE.
10	BD PPI: INDL. PRODUCTS, TOTAL, SOLD ON THE DOMESTIC MARKET NADJ	1	2	BDPROPRCF

11	BD CONSUMER CONFIDENCE INDICATOR - GERMANY SADJ	0	1	BDCNFCONQ
12	BD HWWI IDX OF WORLD MKT.PRC.OF RAW MATS,EURO AREA: EXCL.ENERGY	1	2	BDIUW501F
13	SPREAD GERMANY: BD LONG TERM GOVERNMENT BOND YIELD 9-10 YEARS MINUS BD 3-MONTH FIBOR	0	1	BDGBOND. - BDOIR076R
	FRANCE			
1	FR INDUSTRIAL PRODUCTION VOLA	1	2	FRIPTOT.G
2	FR UNEMPLOYMENT RATE, TOTAL SADJ	0	2	FRESUNEMO
3	FR UNEMPLOYMENT (HARMONIZED): TOTAL TRND	1	2	FRESQT8JT
4	FR BANQUE DE FRANCE SVY.: BUSINESS SENTIMENT INDICATOR(CAL ADJ)	1	1	FRSURCBSQ
5	FR SURVEY: MFG. OUTPUT - ORDER BOOK & FOREIGN DEMAND SADJ	0	1	FRSURFMPQ
6	FR SURVEY: MFG. OUTPUT - FINISHED GOODS INVENTORIES SADJ	0	1	FRSURSMPQ
7	FR SHARE PRICE INDEX - SBF 250 NADJ	1	2	FRSHRPRCF
8	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
9	BD HWWA INDEX OF WORLD MARKET PRICES OF RAW MATS, EURO AREA NADJ	1	2	BDHWWAINF
10	FR SHARE PRICE INDEX - SBF 250 NADJ	1	2	FRSHRPRCF
11	FR REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	FROCC011
12	FR AVERAGE COST OF FUNDS FOR BANKS / EURO REPO RATE	0	1	FRPRATE.
13	SPREAD: FR GOVERNMENT GUARANTEED BOND YIELD (EP) NADJ MINUS FR CAPITAL MARKET YIELDS-13-WEEK TREASURY BILLS,MO.WGHTD.AVG.	0	1	FRGBOND.-FRGBILL3
	ITALY			
1	IT INDUSTRIAL PRODUCTION VOLA	1	2	ITIPTOT.G
2	IT UNEMPLOYMENT RATE, TOTAL SADJ	0	2	ITESUNEMO
3	IT UNEMPLOYMENT VOLA	1	2	ITESTUNPO
4	IT IND.: OVERALL - EMPL EXPECT SADJ	0	1	ITTTA7BSQ
5	IT NEW RESIDENTIAL BUILDINGS - COST INDEX NADJ	1	2	ITECEIBCF
6	IT DISCOUNT RATE / SHORT TERM EURO REPO RATE	0	1	ITPRATE.
7	IT MILAN COMIT GENERAL SHARE PRICE INDEX (EP) NADJ	1	2	ITSHRPRCF
8	IT REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	ITOCC011
9	IT PPI - LINKED & REBASED NADJ	1	2	ITPROPRAF
10	IT ECONOMIC SENTIMENT INDICATOR VOLA	1	1	ITEUSESIG
11	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
12	SPREAD: IT GOVERNMENT BOND GROSS YIELD (RENDISTATO) (EP) MINUS ITALY T-BILL AUCT. GROSS 3 MONTH - MIDDLE RATE	0	1	ITGBOND.-ITBT03G
	JAPAN			
1	JP INDUSTRIAL PRODUCTION - MINING & MANUFACTURING VOLA	1	2	JPIPTOT.G
2	JP UNEMPLOYMENT RATE (METHO BREAK MAR 2011) SADJ	0	2	JPUN%TOTQ
3	JP EMPLOYED PERSONS (METHO BREAK MAR 2011) VOLA	1	1	JPEMPTOTO
4	JP OPERATING RATIO - MANUFACTURING SADJ	1	1	JPCAPUTLQ
5	JP MONTHLY WORKERS SAVINGS & INSURANCE RATE NADJ	0	1	JPPERSAV
6	JP NEW HOUSING CONSTRUCTION STARTED (AR) VOLA	1	2	JPHOUSE.O
7	JP TOKYO STOCK EXCHANGE - TOPIX (EP) NADJ	1	2	JPSHRPRCF
8	JP JAPANESE YEN REAL EFFECTIVE EXCHANGE RATE INDEX NADJ	1	2	JPXTW..RF
9	JP DOMESTIC CORPORATE GOODS PRICE INDEX(DCGPI) NADJ	1	2	JPPROPRCF
10	JP LEADING INDICATORS - CONSUMER CONFIDENCE INDEX NADJ	0	1	JPLEDCCIR
11	JP BASIC DISCOUNT & LOAN RATE (ODR PRIOR TO JAN 01)	0	1	JPDISCRT
12	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
13	JP NEWLY ISSUED GOVERNMENT BONDS YIELD (10 YEARS) NADJ - JP INTEREST RATES: GOVERNMENT SECURITIES, TREASURY BILLS NADJ	0	1	JPNISGBY - JPI60C..

Table B3: Large-sized Datasets

	Variable Name	Log vs Level	Transformation	Datastream code
	US			
1	BD HWWA INDEX OF WORLD MARKET PRICES OF RAW MATS, EURO AREA NADJ	1	2	BDHWWAINF
2	CN EXCHANGE RATE END PERIOD NADJ	0	2	CNOCC016
3	EK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	1	EKOCC011
4	NYSE COMPOSITE - PRICE INDEX	1	2	NYSEALL
5	S&P 500 COMPOSITE - PRICE INDEX	1	2	S&PCOMP
6	US TREASURY YIELD 10 YEAR MINUS US TREASURY BILL RATE - 3 MONTH (EP)	0	1	spread
7	SW EXCHANGE RATE END PERIOD NADJ	0	2	SWOCC016
8	UK MONTH AVERAGE SPOT EXCHANGE RATE, EUR INTO USD VOLN	0	2	UKAERD..P
9	UK LONDON GOLD PRICE - P.M. FIXING (EP)	1	2	UKGOLDP.
10	US COMMERCIAL BANK ASSETS - LOANS & LEASES IN BANK CREDIT CURA	1	1	USBANKLPB
11	US COMMERCIAL BANK ASSETS - COMMERCIAL & INDUSTRIAL LOANS CURA	1	2	USBCACI.B
12	US COMMERCIAL BANK ASSETS - U.S. GOVERNMENT SECURITIES CURA	1	2	USBCAG..B
13	US COMMERCIAL BANK ASSETS - CONSUMER LOANS CURN	1	1	USBCALC.A
14	US COMMERCIAL BANK ASSETS - REAL ESTATE LOANS CURA	1	1	USBCARE.B
15	US COMMERCIAL BANK ASSETS - SECURITIES IN BANK CREDIT CURA	1	2	USBCAS..B
16	US CAPACITY UTILIZATION RATE - ALL INDUSTRY SADJ	0	1	USCAPUTLQ
17	US CHICAGO FED MIDWEST MANUFACTURING INDEX NADJ	1	2	USCFMMI.F
18	US ISM PURCHASING MANAGERS INDEX (MFG SURVEY) SADJ	0	1	USCNFBUSQ
19	US CHAIN-TYPE PRICE INDEX FOR PCE LESS FOOD & ENERGY SADJ	1	1	USCNXFECE
20	US CHAIN-TYPE PRICE INDEX FOR PCE - DURABLES SADJ	1	1	USCONDUCE
21	US PERSONAL CONSUMPTION EXPENDITURES - DURABLES (AR) CURA	1	1	USCONDURB
22	US CHAIN-TYPE PRICE INDEX FOR PCE - NONDURABLE GOODS SADJ	1	1	USCONNDCE
23	US PERSONAL CONSUMPTION EXPENDITURES - NONDURABLES (AR) CURA	1	1	USCONNDRB
24	US CPI - ALL URBAN: ALL ITEMS SADJ	1	1	USCONPRCE
25	US CHAIN-TYPE PRICE INDEX FOR PCE - SERVICES SADJ	1	1	USCONSRCE
26	US PERSONAL CONSUMPTION EXPENDITURES - SERVICES (AR) CURA	1	1	USCONSRVB
27	US CHAIN-TYPE PRICE INDEX FOR PERSONAL CONSMPTN.EXPENDITURE SADJ	1	1	USCP...CE
28	US CPI - APPAREL SADJ	1	1	USCPAPPLE
29	US CPI - COMMODITIES SADJ	1	1	USCPCOMME
30	US CPI - ALL ITEMS LESS FOOD & ENERGY (CORE) SADJ	1	1	USCPCOREE
31	US CPI - DURABLES SADJ	1	1	USCPD...E
32	US CPI - ALL ITEMS LESS FOOD NADJ	1	1	USCPEXCFF
33	US CPI - FOOD & BEVERAGES NADJ	1	1	USCPFB..F
34	US CPI - HOUSING NADJ	1	1	USCPH...F
35	US CPI - MEDICAL CARE SADJ	1	1	USCPMEDCE
36	US CPI - SERVICES SADJ	1	1	USCPS...E
37	US CPI - TRANSPORTATION SADJ	1	2	USCPTRANE
38	US CPI - ALL ITEMS LESS SHELTER NADJ	1	1	USCPXHS.F
39	US CPI - ALL ITEMS LESS MEDICAL CARE NADJ	1	1	USCPXMEDF
40	US CAPACITY UTILIZATION - MANUFACTURING VOLA	0	1	USCUMANUG
41	US PCE: DURB - NEW AUTOS CURA	1	1	USDNEARCB
42	US US $ NOMINAL EFFECTIVE EXCHANGE RATE	1	2	USE$EF..
43	US EMPLOYED - MINING VOLA	1	2	USEM21..O
44	US EMPLOYED - UTILITIES VOLA	1	1	USEM22..O
45	US EMPLOYED - CONSTRUCTION VOLA	1	2	USEM23..O
46	US EMPLOYED - WHOLESALE TRADE VOLA	1	1	USEM42..O
47	US EMPLOYED - OTHER SERVICES VOLA	1	1	USEM81..O
48	US EMPLOYED - PROFESSIONAL & BUSINESS SERVICES VOLA	1	1	USEMIB..O
49	US EMPLOYED - EDUCATION & HEALTH SERVICES VOLA	1	1	USEMIE..O
50	US EMPLOYED - FINANCIAL ACTIVITIES VOLA	1	1	USEMIF..O
51	US EMPLOYED - GOVERNMENT VOLA	1	2	USEMIG..O
52	US EMPLOYED - LEISURE & HOSPITALITY VOLA	1	1	USEMIL..O
53	US EMPLOYED - DURABLE GOODS VOLA	1	2	USEMIMD.O
54	US EMPLOYED - NONDURABLE GOODS VOLA	1	2	USEMIMN.O
55	US EMPLOYED - RETAIL TRADE VOLA	1	1	USEMIR..O

56	US EMPLOYED - TRANSPORTATION & WAREHOUSING VOLA	1	2	USEMIW..O
57	US EMPLOYED - NONFARM INDUSTRIES TOTAL (PAYROLL SURVEY) VOLA	1	1	USEMPALLO
58	US EMPLOYED - GOODS-PRODUCING VOLA	1	2	USEMPG..O
59	US EMPLOYED - MANUFACTURING VOLA	1	2	USEMPMANO
60	US EMPLOYED - PRIVATE SERVICE-PROVIDING VOLA	1	1	USEMPP..O
61	US FEDERAL FUNDS RATE (MONTHLY AVERAGE)	0	1	USFDFUND
62	US PHILADELPHIA FED OUTLOOK SURVEY-DIFFUSION INDEX,NO EMPLOYEES	0	1	USFRBPE.
63	US PHILADELPHIA FED OUTLOOK SURVEY-DIFFUSION INDEX,AVG WORKWEEK	0	1	USFRBPHW
64	US PHILADELPHIA FED OUTLOOK SURVEY-DIFFUSION INDEX,MFG. SADJ	0	1	USFRBPIM
65	US PHILADELPHIA FED OUTLOOK SURVEY-DIFFUSION INDEX,INVENTORIES	0	1	USFRBPIN
66	US PHILADELPHIA FED OUTLOOK SURVEY-DIFFUSION INDEX,NEW ORDERS	0	1	USFRBPON
67	US PHILADELPHIA FED OUTLOOK SURVEY-DIFFUSION INDEX,PRICES PAID	0	1	USFRBPPP
68	US PHILADELPHIA FED OUTLOOK SURVEY-DIFFUSION INDEX,PRICES REC'D	0	1	USFRBPPR
69	US PHILADELPHIA FED OUTLOOK SURVEY-DIFFUSION INDEX,SHIPMENTS	0	1	USFRBPSH
70	US TREASURY BILL RATE - 3 MONTH (EP)	0	1	USGBILL3
71	(SA) US FEDERAL GOVERNMENT BUDGET BALANCE CURN	0	1	USGOVBALA
72	US AVG WKLY HOURS - MANUFACTURING VOLA	0	1	USHKIM..O
73	US AVG WKLY HOURS - TOTAL PRIVATE NONFARM VOLA	0	2	USHKIP..O
74	US NEW PRIVATE HOUSING UNITS AUTHORIZED BY BLDG.PERMIT (AR) VOLA	1	2	USHOUSATE
75	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA	1	2	USHOUSE.O
76	US SALES OF NEW ONE FAMILY HOUSES (AR) VOLA	1	2	USHOUSESE
77	US NEW ONE-FAMILY HOUSES FOR SALE AT END OF PERIOD VOLA	1	1	USHSALE1O
78	US AVG OVERTIME HOURS - MANUFACTURING VOLA	0	2	USHXPMANO
79	US INDEX OF CONSUMER CONFIDENCE SADJ	1	1	USINDCONQ
80	US INDL PROD - MANUFACTURED HOME (MOBILE HOME) VOLA	1	2	USIP321HG
81	US INDL PROD - MOTOR VEHICLES & PARTS NAICS=3361-3 VOLA	1	2	USIP33MVG
82	US INDL PROD - SEMICONDUCTOR & OTHER ELEC COMP VOLA	1	2	USIPELECG
83	US GROSS VALUE OF PRODUCTION - FINAL PRODUCTS (AR) CONA	1	2	USIPFINLD
84	US INDL PROD - BUSINESS EQUIPMENT VOLA	1	2	USIPMBUQG
85	US INDL PROD - CONSUMER GOODS VOLA	1	1	USIPMCOGG
86	US INDL PROD - DURABLE CONSUMER GOODS VOLA	1	2	USIPMDUCG
87	US INDL PROD - NONENERGY DURABLE GOODS MATERIALS VOLA	1	2	USIPMDUMG
88	US INDL PROD - ENERGY, TOTAL VOLA	1	1	USIPMENTG
89	US INDL PROD - DURABLE MFG (NAICS) VOLA	1	2	USIPMFD.G
90	US INDL PROD - MFG (NAICS) VOLN	1	2	USIPMFG.H
91	US INDL PROD - NONDURB MFG (NAICS) VOLA	1	1	USIPMFN.G
92	US INDL PROD-MAT EX ENERGY,MOTOR VEH,COMP,COMM EQ,& SEMICONDU	1	2	USIPMMXEG
93	US INDL PROD - NONDURABLE CONSUMER GOODS VOLA	1	1	USIPMNOCG
94	US INDL PROD - NONDURABLE NONENERGY CONSUMER GOODS VOLA	1	1	USIPMNONG
95	US INDL PROD - FINAL PRODUCTS & NONINDUSTRIAL SUPPLIES VOLA	1	1	USIPMPROG
96	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA	1	2	USIPTOT.G
97	US INDL PROD - ELECTRIC & GAS UTILITIES VOLA	1	1	USIPUTL.G
98	US INDL UTILIZATION - DURABLE MFG (NAICS) SADJ	0	1	USIUMFD.Q
99	US INDL UTILIZATION - NONDURABLE MFG (NAICS) SADJ	0	1	USIUMFN.Q
100	US INDL UTILIZATION-MFG.EXC.COMPUTERS,COMM,& SEMICONDUCTORS SADJ	0	1	USIUMFXCQ
101	US INDL UTILIZATION - SELECTED HIGH-TECHNOLOGY INDUSTRIES SADJ	0	1	USIUMHITQ
102	US INDL UTILIZATION - MINING SADJ	0	1	USIUMIN.Q
103	US INDL UTILIZATION - ELECTRIC & GAS UTILITIES SADJ	0	1	USIUUTL.Q
104	US CIVILIAN LABOR FORCE PARTICIPATION RATE (16 YRS & OVER) SADJ	0	2	USLABFR%E
105	US MONETARY BASE CURN	1	2	USM0....A
106	US MONEY SUPPLY M1 CURA	1	2	USM1....B
107	US MONEY SUPPLY M2 CURA	1	1	USM2....B
108	US ISM MANUFACTURERS SURVEY: SUPPLIER DELIVERY INDEX SADJ	0	1	USNAPMDL
109	US ISM MANUFACTURERS SURVEY: EMPLOYMENT INDEX SADJ	0	1	USNAPMEM
110	US ISM MANUFACTURERS SURVEY: INVENTORIES INDEX NADJ	0	1	USNAPMIV
111	US ISM MANUFACTURERS SURVEY: NEW ORDERS INDEX SADJ	0	1	USNAPMNO
112	US NONBORROWED RESERVES OF DEPOSITORY INSTS, CHANGE NADJ. CURN	0	2	USNBRRSUA
113	US PRIVATE CONSTRUCTION EXPENDITURES - TOTAL (AR) CURA	1	1	USNCPRIVB
114	US CONSTRUCTION EXPENDITURES - TOTAL (AR) CURA	1	1	USNEWCONB
115	US SALES OF TOTAL MFC GOODS (VALUE) CURA	1	1	USOSLI09B

116	US PERSONAL CONSUMPTION EXPENDITURES (AR) CURA	1	1	USPERCONB
117	US DISPOSABLE PERSONAL INCOME (AR) CURA	1	1	USPERDISB
118	US CHICAGO PURCHASING MANAGER BUSINESS BAROMETER (SA) SADJ	0	1	USPMCHBB
119	US PPI - CRUDE MATERIALS LESS ENERGY SADJ	1	2	USPPICMXE
120	US PPI - FINISHED GOODS, EXCLUDING FOODS SADJ	1	1	USPPIFXFE
121	US PPI - FINISHED GOODS LESS FOODS & ENERGY (CORE) SADJ	1	1	USPPIGFFE
122	US PPI - CRUDE NONFOOD MATERIALS LESS ENERGY SADJ	1	2	USPPINXEE
123	US PPI - FINISHED GOODS SADJ	1	1	USPROPRCE
124	US PPI - CRUDE MATERIALS SADJ	1	2	USPSLMCLE
125	US PPI - CRUDE NONFOOD MATERIALS SADJ	1	2	USPSMNF.E
126	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ	1	2	USSHRPRCF
127	US STANDARD AND POORS' 500 COMPOSITE - DIVIDEND YLD	0	2	USSPDIVY
128	US STANDARD AND POORS' 500 COMPOSITE - REAL P/E RATIO	0	2	USSPRPER
129	US TOTAL RESERVES OF DEPOSITORY INSTS,REQUIRED CHANGE NADJ. CURN	1	2	USTOTRSUA
130	US TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 1 YEAR	0	1	USTRCN1.
131	US TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 10 YEAR	0	1	USTRCN10
132	US TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 5 YEAR	0	1	USTRCN5.
133	US TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 7 YEAR	0	1	USTRCN7.
134	US UMICH CSS: CONSUMER SENTIMENT - EXPECTATIONS VOLN	1	1	USUMCONEH
135	US UNEMPLOYMENT RATE SADJ	0	2	USUN%TOTQ
136	US UNEMPLOYED FOR 5 TO 14 WEEKS VOLA	1	1	USUNWK14O
137	US UNEMPLOYED FOR 15 WEEKS OR MORE VOLN	1	1	USUNWK15P
138	US UNEMPLOYED FOR 15 TO 26 WEEKS VOLA	1	2	USUNWK26O
139	(SA) US UNEMPLOYED FOR LESS THAN 5 WEEKS VOLN	1	2	USUNWK5.P
140	US AVERAGE (MEAN) DURATION OF UNEMPLOYMENT (IN WEEKS) VOLN	0	1	USUNWKAVP
141	US AVG HRLY EARN PROD WRKRS-MANUFACTURING CURN	0	2	USWAGMANA
142	US WKLY PAYROLL INDEX - TRANSPORTATION & WAREHOUSING VOLA	1	1	USWKIW..G
143	US PPI - FINISHED CONSUMER GOODS NADJ	1	2	USWPCONFF
144	US AVG HRLY EARN - CONSTRUCTION CURA	0	2	USWR23..B
145	US AVG HRLY EARN - WHOLESALE TRADE CURA	0	2	USWR42..B
146	US AVG HRLY EARN - OTHER SERVICES CURA	0	2	USWR81..B
147	US AVG HRLY EARN - PROFESSIONAL & BUSINESS SERVICES CURA	0	2	USWRIB..B
148	US AVG HRLY EARN - EDUCATION & HEALTH SERVICES CURA	0	2	USWRIE..B
149	US AVG HRLY EARN - FINANCIAL ACTIVITIES CURA	0	2	USWRIF..B
150	US AVG HRLY EARN - TOTAL PRIVATE NONFARM CURA	0	2	USWRIP..B
151	US AVG HRLY EARN - RETAIL TRADE CURA	0	2	USWRIR..B
152	US UK £ TO US $	0	1	USX$UK£.
153	US TREASURY BILL SECONDARY MARKET RATE ON DISCOUNT BASIS-6 MONTH	0	1	USYTB6SM
154	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
155	WILSHIRE 5000 TOTAL MARKET - PRICE INDEX	1	2	WIL5TMK
	UK			
1	BD LONG TERM GOVERNMENT BOND YIELD - 9-10 YEARS	0	2	BDGBOND.
2	BD HWWA INDEX OF WORLD MARKET PRICES OF RAW MATS, EURO AREA NADJ	1	2	BDHWWAINF
3	EK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	1	EKOCC011
4	NYSE COMPOSITE - PRICE INDEX	1	2	NYSEALL
5	S&P 500 COMPOSITE - PRICE INDEX	1	2	S&PCOMP
6	UK YIELD 10-YEAR MINUS UK DISCOUNT RATE 3-MONTH TREASURY BILLS	0	1	UKOIR080R - UKOIR077R
7	UK MONTH AVERAGE SPOT EXCHANGE RATE, EUR INTO USD VOLN	0	2	UKAERD..P
8	UK TREASURY BILLS: DISCOUNT RATE 3M	0	1	UKAJNB..
9	UK MONTHLY AVERAGE SPOT EXCHANGE RATES, STERLING INTO EURO	0	2	UKASERM.
10	UK AVERAGE SPOT EXCHANGE RATE: UK TO US $ VOLN	0	1	UKAUSS..P
11	UK TOTAL CLAIMANT COUNT VOLA	1	2	UKBCJD..
12	UK CLAIMANT COUNT RATE, ALL SADJ	0	2	UKBCJE..
13	UK CBI MONTHLY ENQUIRY: VOLUME OF EXPECTED OUTPUT - BALANCE NADJ	0	1	UKCBIOPB
14	UK LSL/ ACAD AVERAGE HOUSE PRICE CURA	1	2	UKFTHPI.B
15	UK GROSS REDEMPTION YIELD ON 20 YEAR GILTS (PERIOD AVERAGE) NADJ	0	1	UKGBOND.
16	UK GFK CONSUMER CONFIDENCE INDEX NADJ	0	1	UKGFKCCNR
17	UK LONDON GOLD PRICE - P.M. FIXING (EP)	1	2	UKGOLDP.
18	UK INTERBANK RATE - 3 MONTH (MONTH AVG)	0	1	UKINTER3
19	UK INDUSTRIAL PRODUCTION INDEX - MANUFACTURING VOLA	1	2	UKIPMAN.G

20	UK INDEX OF PRODUCTION - ALL PRODUCTION INDUSTRIES VOLA	1	2	UKIPTOT.G
21	UK IOP: B: MINING AND QUARRYING VOLA	1	2	UKK224..G
22	UK IOP: CB: MFG.OF TEXTILES,WEARING APPAREL & LEATHER PRODS.	1	1	UKK22P..G
23	UK IOP: CC: MANUFACTURE OF WOOD & PAPER PRODS, AND PRINTING VOLA	1	2	UKK22T..G
24	UK IOP: CE: MANUFACTURE OF CHEMICALS AND CHEMICAL PRODUCTS VOLA	1	2	UKK22Z..G
25	UK IOP: CG: MFG.RUBBER & PLASTICS PRODS,& OTHER NON-METALLIC	1	2	UKK23B..G
26	UK IOP: CH: MANUFACTURE OF BASIC METALS AND METAL PRODUCTS VOLA	1	2	UKK23G..G
27	UK IOP: CI:MANUFACTURING OF COMPUTER,ELECTRONIC & OPTICAL PRODS.	1	2	UKK23N..G
28	UK IOP: CK: MANUFACTURE OF MACHINERY AND EQUIPMENT N.E.C. VOLA	1	1	UKK23R..G
29	UK IOP: CL: MANUFACTURE OF TRANSPORT EQUIPMENT VOLA	1	1	UKK23T..G
30	UK MONEY SUPPLY M0: NOTES & COINS IN CIRC.OUTSIDE BANK OF ENGLAN	1	2	UKM0....B
31	UK LFS: IN EMP.: AGED 16+: ANNUAL = SPRING QUARTER(MAR-MAY) VOLA	1	2	UKMGRZ..O
32	UK LFS: UNEMPLOYED: AGED 16+ VOLA	1	2	UKMGSC..O
33	UK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	UKOCC011
34	UK EXCHANGE RATE MONTHLY AVERAGE NADJ	0	1	UKOCC015
35	UK DISCOUNT RATE 3-MONTH TREASURY BILLS (STERLING) NADJ	0	1	UKOIR077R
36	UK BANK OF ENGLAND BASE RATE (EP)	0	1	UKPRATE.
37	UK PPI - OUTPUT OF MANUFACTURED PRODUCTS (HOME SALES) NADJ	1	1	UKPROPRCF
38	UK RPI - ALL ITEMS EXCLUDING MORTGAGE INTEREST NADJ	1	1	UKRPAXMIF
39	UK FT ALL SHARE INDEX (EP) NADJ	1	2	UKSHRPRCF
40	UK UNEMPLOYMENT RATE SADJ	0	2	UKUN%TOTQ
41	UK JAPANESE YEN TO UK	1	2	UKXYEN..
42	UK LFS: TOTAL ACTUAL WEEKLY HOURS WORKED, ALL VOLA	1	1	UKYBUS..O
43	US CPI - ALL URBAN: ALL ITEMS SADJ	1	1	USCONPRCE
44	US EMPLOYED - NONFARM INDUSTRIES TOTAL (PAYROLL SURVEY) VOLA	1	2	USEMPALLO
45	US FEDERAL FUNDS RATE (MONTHLY AVERAGE)	0	1	USFDFUND
46	US TREASURY BILL RATE - 3 MONTH (EP)	0	1	USGBILL3
47	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA	1	2	USHOUSE.O
48	zUS INDL PROD - AUTOMOBILE VOLA	1	1	USIP336AG
49	US GROSS VALUE OF PRODUCTION - AUTOMOTIVE PRODUCTS (AR) CONA	1	2	USIPAUTOD
50	US INDL PROD - DURABLE CONSUMER GOODS VOLA	1	2	USIPMDUCG
51	US INDL PROD - MFG (NAICS) VOLN	1	2	USIPMFG.H
52	US INDL PROD - NONDURABLE CONSUMER GOODS VOLA	1	2	USIPMNOCG
53	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA	1	2	USIPTOT.G
54	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ	1	2	USSHRPRCF
55	US STANDARD AND POORS' 500 COMPOSITE - DIVIDEND YLD	0	2	USSPDIVY
56	US UNEMPLOYED (16 YRS & OVER) VOLA	1	2	USUNPTOTO
57	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
58	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
59	WILSHIRE 5000 TOTAL MARKET - PRICE INDEX	1	2	WIL5TMK
	EUROZONE			
1	BD LONG TERM GOVERNMENT BOND YIELD - 9-10 YEARS	0	2	BDGBOND.
2	BD HWWA INDEX OF WORLD MARKET PRICES OF RAW MATS, EURO AREA NADJ	1	1	BDHWWAINF
3	BD DISCOUNT RATE / SHORT TERM EURO REPO RATE	0	2	BDPRATE.
4	CH EXPORTS CURN	1	2	CHEXPGDSA
5	CH INDUSTRIAL PRODUCTION INDEX VOLN	1	2	CHIPTOT.H
6	CH GOLD AND FOREIGN RESERVES - FOREIGN RESERVE CURN	1	2	CHRESERVA
7	EURO STOXX - PRICE INDEX	1	2	DJEURST
8	EK IND.: CMPTR, ELECTRONIC & OPTICAL PRDS - EXP ORD BOOKS SADJ	0	1	EK26.3.BQ
9	EK IND.: ELECTRICAL EQP - EXP ORD BOOKS SADJ	0	1	EK27.3.BQ
10	EK CNSTR.: TOT BLDG - EMPL EXPECT. SADJ	0	2	EK41.4.BQ
11	EK CNSTR.: TOT BLDG - PRICE EXPECT. SADJ	0	2	EK41.5.BQ
12	EK CONSTRUCTION SURVEY: ORDER BOOK POSITION (EA) SADJ	0	2	EK45.3BSQ
13	EK CONSTRUCTION SURVEY: EMPLOYMENT EXPECTATIONS (EA) SADJ	0	2	EK45.4BSQ
14	EK CONSUMER CONFIDENCE INDICATOR (EA) SADJ	0	2	EKCNFCONQ
15	EK IND.: CONSUMER GDS - PROD EXPECT SADJ	0	1	EKCNS5.BQ
16	EK IND.: CONSUMER GDS - SELL PRICE EXPECT SADJ	0	1	EKCNS6.BQ
17	EK IND.: CONSUMER GDS - EMPL EXPECT SADJ	0	2	EKCNS7.BQ
18	EK IND.: DURABLE CONSUMER GDS - EXP ORD BOOKS SADJ	0	2	EKCUR3.BQ
19	EK ECB HARMONISED COMPETITIVENESS INDICATOR - EURO AREA NADJ	1	2	EKECBHCIF

20	EK NEW RESIDENTIAL BUILDINGS - COST INDEX (EA18) NADJ	1	2	EKCECEIBCF
21	EK INDUSTRIAL PRODUCTION - CONSTRUCTION (EA18) VOLA	1	2	EKESCONMG
22	EK CPI - ENERGY (%YOY) (EA18) NADJ	0	1	EKESCPEN%
23	EK CPI - FOOD INCLUDING ALCOHOL & TOBACCO (%YOY) (EA18) NADJ	0	1	EKESCPFT%
24	EK CPI - SERVICES EXCLUDING GOODS (EA18) NADJ	1	2	EKESCPSVF
25	EK CPI - TRANSPORT (%YOY) (EA18) NADJ	0	1	EKESCPTP%
26	EK CPI-HOUSING,WATER,ELECTRICITY,GAS & OTH.FUELS(%YOY)(EA18)	0	2	EKESCPUT%
27	EK INDUSTRIAL PRODN. - CONSUMER NON DURABLES (%MOM) (EA18) SADJ	0	1	EKESICN%Q
28	EK INDUSTRIAL PRODUCTION - CONSUMER DURABLES (%MOM) (EA18) SADJ	0	1	EKESICO%Q
29	EK INDUSTRIAL PRODUCTION - CAPITAL GOODS (%MOM) (EA18) SADJ	0	1	EKESICT%Q
30	EK INDUSTRIAL PRODUCTION - ENERGY (EA18) VOLA	1	2	EKESIENGG
31	EK INDUSTRIAL PRODUCTION - INTERMEDIATE GOODS (%MOM) (EA18) SADJ	0	1	EKESIIT%Q
32	EK UNEMPLOYMENT (EA18) VOLA	1	2	EKESTUNPO
33	EK INDUSTRY SURVEY: EXPORT ORDER-BOOK LEVELS (EA) SADJ	0	1	EKEUIMF3Q
34	EK INDUSTRY SURVEY: PRODUCTION EXPECTATIONS (EA) SADJ	0	1	EKEUIMF5Q
35	EK INDUSTRY SURVEY: EMPLOYMENT EXPECTATIONS (EA) SADJ	0	1	EKEUIMF7Q
36	(SA) EK CONSTRUCTION SURVEY: EMPLOYMENT EXPECTATIONS (EA) NADJ	0	2	EKEUSBEMR
37	EK CONSTRUCTION SURVEY: PRICE EXPECTATIONS (EA) NADJ	0	1	EKEUSBPRR
38	EK ECONOMIC SENTIMENT INDICATOR (EA18) VOLA	1	1	EKEUSESIG
39	EK INDUSTRY SURVEY: ORDER BOOK POSITION (EA) NADJ	0	1	EKEUSIOBR
40	EK SERVICES SVY- TOTAL: DEMAND - NEXT QTR (EA) SADJ	0	1	EKEUSNDXQ
41	EK INDUSTRIAL PRODUCTION: MANUFACTURING (EA18) VOLA	1	2	EKIPMAN.G
42	EK INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION (EA18) VOLA	1	2	EKIPTOT.G
43	EK IND.: INTERMEDIATE GDS - EXP ORD BOOKS SADJ	0	1	EKITM3.BQ
44	EK IND.: INTERMEDIATE GDS - PROD EXPECT SADJ	0	1	EKITM5.BQ
45	EK IND.: INTERMEDIATE GDS - SELL PRICE EXPECT SADJ	0	1	EKITM6.BQ
46	EK IND.: INTERMEDIATE GDS - EMPL EXPECT SADJ	0	1	EKITM7.BQ
47	EK IND.: INVESTMENT GDS - EXP ORD BOOKS SADJ	0	1	EKIVE3.BQ
48	EK IND.: INVESTMENT GDS - PROD EXPECT SADJ	0	1	EKIVE5.BQ
49	EK IND.: INVESTMENT GDS - SELL PRICE EXPECT SADJ	0	1	EKIVE6.BQ
50	EK IND.: INVESTMENT GDS - EMPL EXPECT SADJ	0	1	EKIVE7.BQ
51	EK MFG - ORDER BOOKS: LEVEL SADJ	0	1	EKOBS078Q
52	EK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	EKOCC011
53	EK RETAIL SURVEY: PRESENT BUSINESS SITUATION (EA) SADJ	0	1	EKTTR1BSQ
54	EK RETAIL SURVEY: VOLUME OF STOCKS (EA) SADJ	0	1	EKTTR2BSQ
55	EK RETAIL SURVEY: INTENTIONS OF PLACING ORDERS (EA) SADJ	0	1	EKTTR3BSQ
56	EK RETAIL SURVEY: EXPECTED BUSINESS SITUATION (EA) SADJ	0	1	EKTTR4BSQ
57	EK RETAIL SURVEY: EMPLOYMENT EXPECTATIONS (EA) SADJ	0	1	EKTTR5BSQ
58	EK RETAIL SURVEY: CONFIDENCE (EA) SADJ	0	1	EKTTR99BQ
59	EK BOP: CURRENT ACCOUNT - GOODS (NET) CURN	0	2	EKVISBOPA
60	EM EURO INTERBANK OFFERED RATE - 3-MONTH	0	2	EMIBOR3.
61	US CORP BONDS MOODYS SEASONED AAA (D) - MIDDLE RATE	0	2	FRCBAAA
62	US CORP BONDS MOODYS SEASONED BAA (D) - MIDDLE RATE	0	2	FRCBBAA
63	FTSE GLOBAL 100 ($) - PRICE INDEX	1	2	FTSEGL$
64	NYSE COMPOSITE - PRICE INDEX	1	2	NYSEALL
65	S&P 500 COMPOSITE - PRICE INDEX	1	2	S&PCOMP
66	SPREAD GERMANY: BD LONG TERM GOVERNMENT BOND YIELD 9-10 YEARS MINUS BD 3-MONTH FIBOR	0	1	BDGBOND. - BDOIR076R
67	UK MONTH AVERAGE SPOT EXCHANGE RATE, EUR INTO USD VOLN	0	2	UKAERD..P
68	UK LONDON GOLD PRICE - P.M. FIXING (EP)	1	2	UKGOLDP.
69	US CPI - ALL URBAN: ALL ITEMS SADJ	1	2	USCONPRCE
70	US FEDERAL FUNDS RATE (MONTHLY AVERAGE)	0	2	USFDFUND
71	US TREASURY BILL RATE - 3 MONTH (EP)	0	2	USGBILL3
72	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA	1	2	USHOUSE.O
73	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA	1	2	USIPTOT.G
74	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ	1	2	USSHRPRCF
75	US STANDARD AND POORS' 500 COMPOSITE - DIVIDEND YLD	0	2	USSPDIVY
76	US UMICH CSS: CONSUMER SENTIMENT - EXPECTATIONS VOLN	1	1	USUMCONEH
77	US UNEMPLOYED (16 YRS & OVER) VOLA	1	2	USUNPTOTO
78	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF

79	WD COMMODITY PRICES: ALL COMMODITIES NADJ	1	2	WDI76ACDF
80	WD COMMODITY PRICES: ENERGY NADJ	1	2	WDI76ENDF
81	WILSHIRE 5000 TOTAL MARKET - PRICE INDEX	1	2	WIL5TMK
	GERMANY			
1	(SA) BD NEW PASSENGER CAR REGISTRATIONS VOLN	1	1	BDCAR...P
2	BD CONSUMER CONFIDENCE INDICATOR - GERMANY SADJ	0	1	BDCNFCONQ
3	BD IND.: CONSUMER GDS - SELL PRICE EXPECT SADJ	0	1	BDCNS6.BQ
4	(SA) BD CONSTRUCTION ORDERS RECEIVED VOLN	1	2	BDCNSTR.H
5	BD CPI: TOTAL (FLASH & FINAL) NADJ	1	1	BDCONPRCF
6	BD NEW ORDERS TO MANUFACTURING - DOMESTIC: CONSUMER GOODS VOLA	1	1	BDDCNORDG
7	BD NEW ORDERS TO MANUFACTURING - DOMESTIC: CAPITAL GOODS VOLA	1	1	BDDCPORDG
8	BD EMPLOYMENT DURATION - SHORT-TERM WORKERS VOLN	1	1	BDEMPSTWP
9	BD CONSTRUCTION PRODUCTION INDEX: CONSTRUCTION VOLA	1	2	BDESCONMG
10	BD INDUSTRY T/O INDEX: MIG - CONSUMER GOODS SADJ	1	1	BDESCYEWE
11	BD CONSTRUCTION PRODUCTION INDEX: CIVIL ENGINEERING WORKS VOLA	1	1	BDESG1GZG
12	BD IPI: MANUFACTURE OF MOTOR VEHICLES VOLA	1	2	BDESI29MG
13	BD IPI: MIG - ENERGY (EXCEPT D AND E) VOLA	1	2	BDESIENXG
14	BD IPI: MIG - CONSUMER GOODS VOLA	1	1	BDESISURG
15	BD INDUSTRIAL PRODUCTION - INTERMEDIATE GOODS VOLA	1	1	BDESPIERG
16	BD INDUSTRIAL PRODUCTION - CAPITAL GOODS VOLA	1	1	BDESPIESG
17	BD INDUSTRY T/O INDEX: MIG - INTERMEDIATE GOODS SADJ	1	1	BDESRF78E
18	BD INDUSTRY T/O INDEX: MIG - CAPITAL GOODS SADJ	1	1	BDESSSOOE
19	BD UNEMPLOYMENT RATE, TOTAL SADJ	0	2	BDESUNEMO
20	BD TOTAL EXPORTS OF GOODS CURN	1	1	BDEXPBOPA
21	BD EXPORTS FOB (PAN BD M0790) CURN	1	1	BDEXPGDSA
22	BD LONG TERM GOVERNMENT BOND YIELD - 9-10 YEARS	0	1	BDGBOND.
23	BD CONSTRUCTION ORDERS RECEIVED - RESIDENTIAL CONSTRUCTION VOLA	1	2	BDHOUSE.G
24	BD HWWA INDEX OF WORLD MARKET PRICES OF RAW MATS, EURO AREA NADJ	1	1	BDHWWAINF
25	BD CNSTR.IND.: CAPACITY UTILIZATION SADJ	0	2	BDIFDCTNQ
26	BD MFG. CONS. DURB.: BUSINESS SIT. NEXT 6 MO. - BAL. SADJ	0	1	BDIFDMDKQ
27	BD MFG. CONS. NON-DURB.: BUSINESS SIT. NEXT 6 MO. - BAL. SADJ	0	1	BDIFDMNKQ
28	BD MFG. CAPITAL GOODS: BUSINESS SIT. - BAL. SADJ	0	1	BDIFDMPAQ
29	BD MFG. CAPITAL GOODS: INVTRY. OF FINISHED GOODS - BAL. SADJ	0	1	BDIFDMPCQ
30	BD MFG. CAPITAL GOODS: BUSINESS SIT. NEXT 6 MO. - BAL. SADJ	0	1	BDIFDMPKQ
31	BD RET.SALE - DURABLES: ASSESSMENT OF BUSINESS SITUATION SADJ	0	1	BDIFRDUAQ
32	BD RET.SALE - DURABLES: ASSESSMENT OF INVENTORIES SADJ	0	1	BDIFRDUCQ
33	BD RET.SALE - NON-DURABLES: ASSESSMENT OF INVENTORIES SADJ	0	1	BDIFRNDCQ
34	BD RET.SALE-BUSINESS EXPECT.NEXT 6 MO.: INCL.MOT.VEH,PETR.ST.	0	1	BDIFRS.LR
35	BD RET.SALE - ASSESSMENT OF BUSINESS SITUATION SADJ	0	1	BDIFRSAAQ
36	BD WHOLESALE OF CONSUMER GOODS: ASSESSMENT OF BUSINESS SITUATION	0	1	BDIFWCOAQ
37	BD WHOLESALE OF FBT: EXPECT.OF BUSINESS DEVELOPMENT IN NEXT 6 MO	0	1	BDIFWFBLQ
38	BD TOTAL IMPORTS OF GOODS CURN	1	1	BDIMPBOPA
39	BD IMPORTS CIF (PAN BD M0790) CURN	1	1	BDIMPGDSA
40	(SA) BD INDUSTRIAL PRODUCTION - BASIC IRON & STEEL VOLN	1	1	BDIPIRSTH
41	BD INDUSTRIAL PRODUCTION INCLUDING CONSTRUCTION (CAL ADJ) VOLA	1	1	BDIPTOT.G
42	BD HWWI IDX OF WORLD MKT.PRC.OF RAW MATS,EURO AREA: EXCL.ENERGY	1	2	BDIUW501F
43	BD HWWI INDEX OF WORLD MKT.PRC.OF RAW MATS.FOR EURO AREA: ENERGY	1	1	BDIUW510F
44	BD MONEY SUPPLY-GERMAN CONTRIBUTION TO EURO M1(PAN BD M0790)	1	2	BDM1....A
45	BD MONEY SUPPLY-GERMAN CONTRIBUTION TO EURO M2(PAN BD M0690)	1	2	BDM2....A
46	BD MONEY SUPPLY-GERMAN CONTRIBUTION TO EURO M3(PAN BD M0690)	1	1	BDM3....A
47	BD YD 10-YR GOVT.BONDS(PROXY-9-10+ YEAR FEDERAL SECURITIES) NADJ	0	1	BDMIR080R
48	BD HARMONISED UNEMPLOYMENT: LEVEL, ALL PERSONS (ALL AGES) VOLA	1	2	BDMLFT15O
49	BD NEW ORDERS: MFG, MANUFACTURE OF ELECTRICAL EQUIP. , DOM. VOLA	1	1	BDNODEEQG
50	BD NEW ORDERS: MFG, MOTOR VEH., TRAILERS&SEMI-TRAIL., DOM. SADJ	1	1	BDNODVEME
51	BD NEW ORDERS: MFG,MOTOR VEH., TRAILERS&SEMI-TRAIL., ABROAD SADJ	1	2	BDNOFVEME
52	BD REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	BDOCC011
53	BD NEW ORDERS TO MFG. - FROM ABROAD: CONSUMER GOODS VOLA	1	1	BDOCNORDG
54	BD DEU CPI ENERGY NADJ	1	2	BDOCP041F
55	BD NEW ORDERS TO MANUFACTURING - FROM ABROAD: CAPITAL GOODS VOLA	1	2	BDOCPORDG
56	BD 3-MONTH FIBOR NADJ	0	1	BDOIR076R

57	BD CLI SPREAD OF IRS NADJ	0	1	BDOL2056R
58	BD ORDERS FOR MFC INTERMEDIATE GOODS (VOLUME) VOLA	1	1	BDOODI51G
59	BD SHARE PRICES: CDAX INDEX NADJ	1	2	BDOSP001F
60	BD PPI: MOTOR FUEL, INCL. AIRCRAFT FUEL NADJ	1	1	BDPPFUMTF
61	BD DISCOUNT RATE / SHORT TERM EURO REPO RATE	0	2	BDPRATE.
62	BD PPI: INDL. PRODUCTS, TOTAL, SOLD ON THE DOMESTIC MARKET NADJ	1	2	BDPROPRCF
63	BD DAX SHARE PRICE INDEX, EP NADJ	1	2	BDSHRPRCF
64	BD IND.T/O: COMPUTER, ELECTRONIC & OPTICAL PRODUCTS, DOM. VOLA	1	2	BDSTDCEOG
65	BD IND.T/O: MOTOR VEH., TRAILERS&SEMI-TRAIL., DOM. VOLA	1	1	BDSTDVEMG
66	BD IND. T/O: CAPITAL GOODS, FGN. SADJ	1	2	BDSTFCAPE
67	BD IND.T/O: COMPUTER, ELECTRONIC & OPTICAL PRODUCTS, FGN. VOLN	1	2	BDSTFCEOH
68	BD IND. T/O: CONS. GOODS, FGN. SADJ	1	2	BDSTFCONE
69	BD IND. T/O: INTERMEDIATE GOODS, FGN. SADJ	1	2	BDSTFINTE
70	BD IND.T/O: MOTOR VEH., TRAILERS&SEMI-TRAIL., FGN. VOLN	1	1	BDSTFVEMH
71	BD MFG ORDERS: COMPUTER,ELECC.&OPT.PRDS,ELECL. EQUIP., FGN. VOLA	1	2	BDUSC588G
72	BD CONSTRUCTION ORDERS RECEIVED-NON-RESIDENTIAL CONSTRUCTION	1	1	BDUSDA19G
73	BD CONSTRUCTION ORDERS RECEIVED - CIVIL ENGINEERING VOLA	1	1	BDUSDA20G
74	BD CPI (EXCLUDING ENERGY) SADJ	1	1	BDUSFB76E
75	BD CONSTRUCTION: MAN-HOURS WORKED CURA	1	2	BDUSMB11B
76	BD TURNOVER IN CONSTRUCTION - TOTAL CURA	0	1	BDUSMB28B
77	BD TURNOVER IN CONSTRUCTION - INDUSTRIAL BUILDING CURA	0	2	BDUSMB31B
78	BD TURNOVER IN CONSTRUCTION - RESIDENTIAL BUILDING CURA	0	2	BDUSMB36B
79	BD TURNOVER IN CONSTRUCTION- PUB SECTOR & ROAD CONSTRUCTION CURA	0	1	BDUSMB37B
80	(SA) BD VACANCIES VOLN	1	2	BDUUCC04P
81	BD REX PRICE INDEX, END OF MONTH CURN	1	2	BDWU035AA
82	BD FULLY TAXED BONDS OUTSTANDING-YIELDS:GT1Y&UP TO 2Y TO MATURIT	0	1	BDWU0898R
83	BD FULLY TAXED BONDS OUTSTANDING-YIELDS:GT5Y&UP TO 6Y TO MATURIT	0	1	BDWU0902R
84	BD FULLY TAXED BONDS OUTSTAND-YIELDS GT 9Y& UP TO 10Y TO MTRY.	0	1	BDWU8608R
85	BD YLDS ON LSTED FEDRL BNDS OUTSTNDG.MATURITY 3-5 YRS AVE.RATE	0	1	BDWU9552R
86	BD YIELDS ON LISTED FED.SEC,DER.FM.TS OF IR,RESID.MTRY.1 YR.	0	1	BDWZ3400
87	CH EXPORTS CURN	1	1	CHEXPGDSA
88	CH INDUSTRIAL PRODUCTION INDEX VOLN	1	1	CHIPTOT.H
89	CH GOLD AND FOREIGN RESERVES - FOREIGN RESERVE CURN	1	1	CHRESERVA
90	EURO STOXX - PRICE INDEX	1	2	DJEURST
91	EK CONSUMER CONFIDENCE INDICATOR (EA) SADJ	0	1	EKCNFCONQ
92	EK INDUSTRIAL PRODUCTION - ENERGY (EA18) VOLA	1	2	EKESIENGG
93	EK INDUSTRY SURVEY: PRODUCTION EXPECTATIONS (EA) SADJ	0	1	EKEUIMF5Q
94	EK INDUSTRIAL PRODUCTION: MANUFACTURING (EA18) VOLA	1	2	EKIPMAN.G
95	EK INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION (EA18) VOLA	1	2	EKIPTOT.G
96	EK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	EKOCC011
97	US CORP BONDS MOODYS SEASONED AAA (D) - MIDDLE RATE	0	1	FRCBAAA
98	US CORP BONDS MOODYS SEASONED BAA (D) - MIDDLE RATE	0	2	FRCBBAA
99	NYSE COMPOSITE - PRICE INDEX	1	2	NYSEALL
100	S&P 500 COMPOSITE - PRICE INDEX	1	2	S&PCOMP
101	SPREAD GERMANY: BD LONG TERM GOVERNMENT BOND YIELD 9-10 YEARS MINUS BD 3-MONTH FIBOR	0	1	BDGBOND. - BDOIR076R
102	UK MONTH AVERAGE SPOT EXCHANGE RATE, EUR INTO USD VOLN	0	2	UKAERD..P
103	UK LONDON GOLD PRICE - P.M. FIXING (EP)	1	2	UKGOLDP.
104	US CPI - ALL URBAN: ALL ITEMS SADJ	1	2	USCONPRCE
105	US FEDERAL FUNDS RATE (MONTHLY AVERAGE)	0	2	USFDFUND
106	US TREASURY BILL RATE - 3 MONTH (EP)	0	2	USGBILL3
107	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA	1	2	USHOUSE.O
108	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA	1	2	USIPTOT.G
109	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ	1	2	USSHRPRCF
110	US STANDARD AND POORS' 500 COMPOSITE - DIVIDEND YLD	0	2	USSPDIVY
111	US UMICH CSS: CONSUMER SENTIMENT - EXPECTATIONS VOLN	1	1	USUMCONEH
112	US UNEMPLOYED (16 YRS & OVER) VOLA	1	2	USUNPTOTO
113	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
114	WILSHIRE 5000 TOTAL MARKET - PRICE INDEX	1	2	WIL5TMK
	FRANCE			

1	BD LONG TERM GOVERNMENT BOND YIELD - 9-10 YEARS	0	2	BDGBOND.
2	BD HWWA INDEX OF WORLD MARKET PRICES OF RAW MATS, EURO AREA NADJ	1	2	BDHWWAINF
3	BD DISCOUNT RATE / SHORT TERM EURO REPO RATE	0	2	BDPRATE.
4	CH GOLD AND FOREIGN RESERVES - FOREIGN RESERVE CURN	1	1	CHRESERVA
5	EK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	1	EKOCC011
6	FR CAPITAL MARKET YIELDS-BOND YIELD,PRIVATE SECTOR(AVERAGE) NADJ	0	1	FR101066
7	FR WHOLESALE COMPOSITE INDICATOR NADJ	1	1	FR579137F
8	FR SURVEY - HOUSEHOLDS, ECONOMIC SITUATION PAST 12M SADJ	0	2	FR857188Q
9	FR SURVEY - HOUSEHOLDS, ECONOMIC SITUATION NEXT 12M SADJ	0	1	FR857189Q
10	FR SURVEY-HOUSEHOLD OPINION ON FUTURE EVOLUTION ON UNEMPLMT.	0	1	FR857190Q
11	FR SURVEY-HOUSEHOLD OPINION ON PAST EVOLUTION OF CONSUMER PRICES	0	1	FR857191Q
12	FR SURVEY-HOUSEHOLD OPINION ON FUTURE EVOLUTION CONSUMER PRICES	0	1	FR857192Q
13	FR SURVEY-HOUSEHOLD OPINION ON IMPORTANT PURCHASE INTENTIONS	0	2	FR857193Q
14	FR SURVEY - HOUSEHOLD OPINION ON PAST FINANCIAL SITUATION SADJ	0	2	FR857196Q
15	FR SURVEY - HOUSEHOLD OPINION ON FUTURE FINANCIAL SITUATION SADJ	0	2	FR857197Q
16	FR MFI LOANS TO RESIDENT PRIVATE SECTOR CURN	1	2	FRBANKLPA
17	FR BDF ASSETS: FRANCE - LOANS CENTRAL GOVERNMENT CURN	0	1	FRBDFFCGA
18	US CORP BONDS MOODYS SEASONED AAA (D) - MIDDLE RATE	0	1	FRCBAAA
19	FR SURVEY: MANUFACTURING OUTPUT LEVEL - GENERAL OUTLOOK SADJ	0	1	FRCNFBUSQ
20	FR UNEMPLOYMENT (HARMONIZED): TOTAL TRND	1	2	FRESQT8JT
21	FR UNEMPLOYMENT RATE, TOTAL SADJ	0	2	FRESUNEMO
22	FR CAPITAL MARKET YIELDS-13-WEEK TREASURY BILLS,MO.WGHTD.AVG.	0	1	FRGBILL3
23	FR GOVERNMENT GUARANTEED BOND YIELD (EP) NADJ	0	1	FRGBOND.
24	FR HOUSEHOLD CONSUMPTION - AUTOMOBILES CONA	0	1	FRHCONAUD
25	FR HOUSEHOLD CONSUMPTION - DURABLE GOODS CONA	0	2	FRHCONDGD
26	FR HOUSEHOLD CONSUMPTION - HOUSEHOLD EQPT CONA	0	2	FRHCONLGD
27	FR HOUSEHOLD CONSUMPTION - MANUFACTURED GOODS CONA	0	2	FRHCONMFD
28	FR HOUSEHOLD CONSUMPTION - ENGINEERED PRODUCTS CONA	0	2	FRHCONMGD
29	FR HOUSEHOLD CONSUMPTION - TEXTILES & LEATHER CONA	0	1	FRHCONTLD
30	FR INDUSTRIAL PRODUCTION VOLA	1	2	FRIPTOT.G
31	FR MFI LIABILITIES: FRANCE - DEPOSITS CENTRAL GOVERNMENT CURN	1	2	FRMFIDFGA
32	FR MFI ASSETS: LOANS - GENERAL GOVERNMENT CURN	1	2	FRMFIFCGA
33	FR REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	FROCC011
34	FR 3-MONTH PIBOR NADJ	0	1	FROIR076R
35	FR AVERAGE COST OF FUNDS FOR BANKS / EURO REPO RATE	0	1	FRPRATE.
36	FR SHARE PRICE INDEX - SBF 250 NADJ	1	2	FRSHRPRCF
37	FR BANQUE DE FRANCE SVY.: BUSINESS SENTIMENT INDICATOR(CAL ADJ)	1	1	FRSURCBSQ
38	FR SURVEY: MFG. OUTPUT - ORDER BOOK & FOREIGN DEMAND SADJ	0	1	FRSURFMPQ
39	FR SURVEY: MANUFACTURING OUTPUT - ORDER BOOK & DEMAND SADJ	0	1	FRSURGMPQ
40	FR SURVEY: MFG. OUTPUT - FINISHED GOODS INVENTORIES SADJ	0	1	FRSURSMPQ
41	FR US $ TO 1 EURO (FRENCH FRANC DERIVED HISTORY PRIOR 1999)	0	2	FRXRUSE.
42	NYSE COMPOSITE - PRICE INDEX	1	2	NYSEALL
43	S&P 500 COMPOSITE - PRICE INDEX	1	2	S&PCOMP
44	SPREAD: FR GOVERNMENT GUARANTEED BOND YIELD (EP) NADJ MINUS FR CAPITAL MARKET YIELDS-13-WEEK TREASURY BILLS,MO.WGHTD.AVG.	0	1	FRGBOND.-FRGBILL3
45	UK MONTH AVERAGE SPOT EXCHANGE RATE, EUR INTO USD VOLN	0	2	UKAERD..P
46	UK LONDON GOLD PRICE - P.M. FIXING (EP)	1	2	UKGOLDP.
47	US CPI - ALL URBAN: ALL ITEMS SADJ	1	1	USCONPRCE
48	US FEDERAL FUNDS RATE (MONTHLY AVERAGE)	0	1	USFDFUND
49	US TREASURY BILL RATE - 3 MONTH (EP)	0	1	USGBILL3
50	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA	1	2	USHOUSE.O
51	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA	1	2	USIPTOT.G
52	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ	1	2	USSHRPRCF
53	US STANDARD AND POORS' 500 COMPOSITE - DIVIDEND YLD	0	2	USSPDIVY
54	US UMICH CSS: CONSUMER SENTIMENT - EXPECTATIONS VOLN	1	1	USUMCONEH
55	US UNEMPLOYED (16 YRS & OVER) VOLA	1	2	USUNPTOTO
56	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
57	WILSHIRE 5000 TOTAL MARKET - PRICE INDEX	1	2	WIL5TMK
	ITALY			
1	ITALY-DS Automobiles - PRICE INDEX	1	2	AUTOSIT

2	Baltic Exchange Dry Index (BDI) - PRICE INDEX	1	2	BALTICF
3	ITALY-DS Banks - PRICE INDEX	1	2	BANKSIT
4	GERMANY BENCHMARK BOND 10 YR (DS) - RED. YIELD	0	1	BDBRYLD
5	BD LONG TERM GOVERNMENT BOND YIELD - 9-10 YEARS	0	1	BDGBOND.
6	BD HWWA INDEX OF WORLD MARKET PRICES OF RAW MATS, EURO AREA NADJ	1	1	BDHWWAINF
7	MNY MKT - 3-MONTH FRANKFURT 'DEAD' - MIDDLE RATE	0	2	BDMNY3M
8	CH EXPORTS CURN	1	1	CHEXPGDSA
9	CH INDUSTRIAL PRODUCTION INDEX VOLN	1	1	CHIPTOT.H
10	CH GOLD AND FOREIGN RESERVES - FOREIGN RESERVE CURN	1	1	CHRESERVA
11	DC WORLD BNK NON-ENERGY COMMODITIY PRICES: LOWER MID INCM CNTRYS	1	2	DCI76AXDF
12	EURO STOXX - PRICE INDEX	1	2	DJEURST
13	EK CONSUMER CONFIDENCE INDICATOR (EA) SADJ	0	1	EKCNFCONQ
14	EK INDUSTRY SURVEY: PRODUCTION EXPECTATIONS (EA) SADJ	0	1	EKEUIMF5Q
15	EK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	EKOCC011
16	ITALY-DS Electricity - PRICE INDEX	1	2	ELECTIT
17	ITALY-DS Eltro/Elec Eq - PRICE INDEX	1	2	ELTNCIT
18	US CORP BONDS MOODYS SEASONED AAA (D) - MIDDLE RATE	0	1	FRCBAAA
19	US CORP BONDS MOODYS SEASONED BAA (D) - MIDDLE RATE	0	2	FRCBBAA
20	ITALY-DS Industrials - PRICE INDEX	1	2	INDUSIT
21	ITALY-DS Tch H/W & Eq - PRICE INDEX	1	2	INFOHIT
22	ITALY-DS Insurance - PRICE INDEX	1	2	INSURIT
23	IT BUSINESS SVY.: ECONOMY IN NEXT 3MOS., NET NADJ	0	1	ITBSINEVR
24	(SA) IT BUSINESS SVY.: SELLING PRICE IN NEXT 3MOS., NET NADJ	0	1	ITBSINSBR
25	ITALY T-BILL AUCT. GROSS 3 MONTH - MIDDLE RATE	0	2	ITBT03G
26	ITALY T-BILL AUCT. GROSS 6 MONTH - MIDDLE RATE	0	2	ITBT06G
27	ITALY T-BILL AUCT. GROSS 12 MONTH - MIDDLE RATE	0	1	ITBT12G
28	(SA) IT NEW PASSENGER CAR REGISTRATIONS VOLN	1	2	ITCAR...P
29	IT BUS.SVY.: CONSUMER GOODS - ORDER BOOKS EXPORT, NET NADJ	0	1	ITCONEXOR
30	IT BUS.SVY.: CONS.GDS.- ECONOMY IN NEXT 3MOS., NET NADJ	0	1	ITCONFECR
31	(SA) IT BUS.SVY.: CONS.GDS.- ORDER BOOKS IN NEXT 3MOS., NET NADJ	0	1	ITCONFOBR
32	(SA) IT BUS.SVY.: CONS.GDS.- PRODUCTION IN NEXT 3MOS., NET NADJ	0	2	ITCONFPRR
33	IT BUS.SVY.: CONS.GDS.- SELLING PRICE IN NEXT 3MOS., NET NADJ	0	1	ITCONFSPR
34	IT BUS.SVY.: CONSUMER GOODS - ORDER BOOKS DOMESTIC, NET NADJ	0	1	ITCONOBBR
35	(SA) IT BUS.SVY.: CONSUMER GOODS - ORDER BOOKS, NET NADJ	0	1	ITCONORDR
36	(SA) IT BUS.SVY.: CONSUMER GOODS - PRODUCTION LEVEL, NET NADJ	0	1	ITCONPRDR
37	(SA) IT BUS.SVY.: CONSUMER GOODS - STOCKS OF FIN.GDS., NET NADJ	0	1	ITCONSFGR
38	IT BUSINESS SVY.: ORDER BOOKS - DOMESTIC, NET NADJ	0	1	ITDOMORDR
39	IT NEW RESIDENTIAL BUILDINGS - COST INDEX NADJ	1	2	ITECEIBCF
40	IT LONG TERM GOVT.BOND YIELDS- MAASTRICHT DEFINITION (AVG.)	0	2	ITESEFIGR
41	(SA) IT ENERGY - CONSUMPTION, ELECTRICITY VOLN	1	2	ITESEIWAP
42	IT UNEMPLOYMENT VOLA	1	2	ITESTUNPO
43	IT UNEMPLOYMENT RATE, TOTAL SADJ	0	2	ITESUNEMO
44	IT ECONOMIC SENTIMENT INDICATOR VOLA	1	1	ITEUSESIG
45	(SA) IT BUSINESS SVY.: ORDER BOOKS IN NEXT 3MOS., NET NADJ	0	1	ITEXPORDR
46	IT BUSINESS SVY.: ORDER BOOKS - EXPORT, NET NADJ	0	1	ITFORORDR
47	IT GOVERNMENT BOND GROSS YIELD (RENDISTATO) (EP)	0	1	ITGBOND.
48	IT BUS.SVY.: INTERMED. GDS.- ORDER BOOKS EXPORT, NET NADJ	0	1	ITINTEXOR
49	IT BUS.SVY.: INTERMED.GDS.- ECONOMY IN NEXT 3MOS., NET NADJ	0	1	ITINTFECR
50	(SA) IT BUS.SVY.: INTERMED.GDS.- ORDER BOOKS IN NEXT 3MOS., NET NADJ	0	1	ITINTFOBR
51	(SA) IT BUS.SVY.: INTERMED.GDS.- PRODUCTION IN NEXT 3MOS., NET NADJ	0	1	ITINTFPRR
52	IT BUS.SVY.: INTERMED.GDS.- SELL.PRICE IN NEXT 3MOS., NET NADJ	0	1	ITINTFSPR
53	IT BUS.SVY.: INTERMED. GDS.- ORDER BOOKS DOMESTIC, NET NADJ	0	1	ITINTOBBR
54	IT BUS.SVY.: INTERMED. GDS.- ORDER BOOKS, NET NADJ	0	1	ITINTORDR
55	IT BUS.SVY.: INTERMED. GDS.- PRODUCTION LEVEL, NET NADJ	0	1	ITINTPRDR
56	IT BUS.SVY.: INTERMED. GDS.- STOCKS OF FIN.GDS., NET NADJ	0	1	ITINTSFGR
57	IT BUS.SVY.:INVESTMENT GOODS - ORDER BOOKS EXPORT, NET NADJ	0	1	ITINVEXOR
58	IT BUS.SVY.: INV.GDS.- ECONOMY IN NEXT 3MOS., NET NADJ	0	1	ITINVFECR
59	(SA) IT BUS.SVY.: INV.GDS.- ORDER BOOKS IN NEXT 3MOS., NET NADJ	0	1	ITINVFOBR
60	(SA) IT BUS.SVY.: INV.GDS.- PRODUCTION IN NEXT 3MOS., NET NADJ	0	1	ITINVFPRR
61	(SA) IT BUS.SVY.: INV.GDS.- SELLING PRICE IN NEXT 3MOS., NET NADJ	0	1	ITINVFSPR

62	IT BUS.SVY.:INVESTMENT GOODS - ORDER BOOKS DOMESTIC, NET NADJ	0	1	ITINVOBBR
63	IT BUS.SVY.:INVESTMENT GOODS - ORDER BOOKS, NET NADJ	0	1	ITINVORDR
64	IT BUS.SVY.:INVESTMENT GOODS - PRODUCTION LEVEL, NET NADJ	0	1	ITINVPRDR
65	IT BUS.SVY.:INVESTMENT GOODS - STOCKS OF FIN.GDS., NET NADJ	0	1	ITINVSFGR
66	IT INDUSTRIAL PRODN.: ELECTRICITY,GAS,STEAM & AIR CONDITIONED	1	2	ITIP350EG
67	IT INDUSTRIAL PRODUCTION: CONSUMER GOODS - DURABLE VOLA	1	2	ITIPCGDRG
68	IT INDUSTRIAL PRODUCTION: CONSUMER GOODS - NON-DURABLE VOLA	1	1	ITIPCGNDG
69	IT INDUSTRIAL PRODN.: CHEMICAL PRODUCTS & SYNTHETIC FIBRES VOLA	1	2	ITIPCHEMG
70	IT INDUSTRIAL PRODN.: COMPUTER,ELECTRONIC & OPTICAL PRODS. VOLA	1	1	ITIPCI0EG
71	IT INDUSTRIAL PRODUCTION: ELECTRICAL EQUIPMENT VOLA	1	2	ITIPCJ0QG
72	IT INDUSTRIAL PRODN.: OTH.MFG,& REPAIR & INSTALL-MACH & EQP VOLA	1	2	ITIPCMOMG
73	IT INDUSTRIAL PRODUCTION: CONSUMER GOODS VOLA	1	2	ITIPCNGDG
74	IT INDUSTRIAL PRODUCTION: ENERGY VOLA	1	2	ITIPENGYG
75	IT INDUSTRIAL PRODUCTION: FOOD, DRINK & TOBACCO VOLA	1	1	ITIPFOODG
76	IT INDUSTRIAL PRODN.: COKE MANUFACTURE & PETROLEUM REFINING VOLA	1	2	ITIPFUELG
77	IT INDUSTRIAL PRODUCTION: INTERMEDIATE GOODS VOLA	1	2	ITIPINTMG
78	IT INDUSTRIAL PRODUCTION: INVESTMENT GOODS VOLA	1	2	ITIPINVTG
79	IT INDUSTRIAL PRODUCTION: MACHINES & MECHANICAL APPARATUS VOLA	1	2	ITIPMACHG
80	IT INDUSTRIAL PRODUCTION: MANUFACTURING VOLA	1	2	ITIPMAN.G
81	IT INDUSTRIAL PRODUCTION: METAL & METAL PRODUCTS VOLA	1	2	ITIPMETLG
82	IT INDUSTRIAL PRODUCTION: EXTRACTION OF MINERALS VOLA	1	2	ITIPMINGG
83	IT INDUSTRIAL PRODUCTION: BASIC PHARMACEUTICAL PRODUCTS VOLA	1	1	ITIPPHARG
84	IT INDUSTRIAL PRODUCTION: RUBBER ITEMS & PLASTIC MATERIALS VOLA	1	2	ITIPRUBRG
85	IT INDUSTRIAL PRODUCTION: TEXTILE & CLOTHING VOLA	1	2	ITIPTEXTG
86	IT INDUSTRIAL PRODUCTION VOLA	1	2	ITIPTOT.G
87	IT INDUSTRIAL PRODUCTION: MEANS OF TRANSPORT VOLA	1	2	ITIPTRNSG
88	IT INDUSTRIAL PRODUCTION: WOOD & WOOD PRODUCTS VOLA	1	2	ITIPWOODG
89	IT BUSINESS SVY.: STOCKS OF FINISHED GOODS, NET NADJ	0	1	ITLEVINVR
90	IT MONEY SUPPLY: M1 - ITALIAN CONTRIBUTION TO THE EURO AREA CURN	1	2	ITM1....A
91	IT MONEY SUPPLY: M2 - ITALIAN CONTRIBUTION TO THE EURO AREA CURN	1	2	ITM2....A
92	IT MONEY SUPPLY: M3 - ITALIAN CONTRIBUTION TO THE EURO AREA CURN	1	2	ITM3....A
93	IT CAR REGISTRATIONS-NEW MEDIUM & HEAVY CML.VEHICLES OVER 3.5T	1	1	ITMCVREGP
94	FTSE ITALIA MIB STORICO - PRICE INDEX	1	2	ITMHIST
95	IT NEW ORDERS SADJ	1	2	ITNEWORDE
96	IT REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	2	ITOCC011
97	IT 3-MONTH INTERBANK RATE ON DEPOSITS NADJ	0	2	ITOIR076R
98	IT DISCOUNT RATE / SHORT TERM EURO REPO RATE	0	1	ITPRATE.
99	(SA) IT BUSINESS SVY.: PRODUCTION IN NEXT 3MOS., NET NADJ	0	1	ITPRDEXPR
100	IT PPI - LINKED & REBASED NADJ	1	2	ITPROPRAF
101	IT MILAN COMIT GENERAL SHARE PRICE INDEX (EP) NADJ	1	2	ITSHRPRCF
102	IT BUSINESS SVY.: ORDER BOOKS, NET NADJ	0	1	ITTOTORDR
103	IT BUSINESS SVY.: PRODUCTION LEVEL, NET NADJ	0	1	ITTOTPRDR
104	IT IND.: OVERALL - EMPL EXPECT SADJ	0	1	ITTTA7BSQ
105	IT ITALIAN LIRE TO US $ (MTH.AVG.)	1	2	ITXRUSD.
106	ITALY-DS Media - PRICE INDEX	1	2	MEDIAIT
107	NYSE COMPOSITE - PRICE INDEX	1	2	NYSEALL
108	ITALY-DS Oil & Gas - PRICE INDEX	1	2	OILGSIT
109	ITALY-DS Pharm & Bio - PRICE INDEX	1	1	PHARMIT
110	S&P 500 COMPOSITE - PRICE INDEX	1	2	S&PCOMP
111	SPREAD: IT GOVERNMENT BOND GROSS YIELD (RENDISTATO) (EP) MINUS ITALY T-BILL AUCT. GROSS 3 MONTH - MIDDLE RATE	0	1	ITGBOND.-ITBT03G
112	ITALY-DS Telecom - PRICE INDEX	1	2	TELCMIT
113	ITALY-DS Market - PRICE INDEX	1	2	TOTMKIT
114	UK MONTH AVERAGE SPOT EXCHANGE RATE, EUR INTO USD VOLN	0	2	UKAERD..P
115	UK LONDON GOLD PRICE - P.M. FIXING (EP)	1	2	UKGOLDP.
116	US CPI - ALL URBAN: ALL ITEMS SADJ	1	2	USCONPRCE
117	US FEDERAL FUNDS RATE (MONTHLY AVERAGE)	0	1	USFDFUND
118	US TREASURY BILL RATE - 3 MONTH (EP)	0	1	USGBILL3
119	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA	1	2	USHOUSE.O
120	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA	1	2	USIPTOT.G

121	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ	1	2	USSHRPRCF
122	US STANDARD AND POORS' 500 COMPOSITE - DIVIDEND YLD	0	2	USSPDIVY
123	US UMICH CSS: CONSUMER SENTIMENT - EXPECTATIONS VOLN	1	1	USUMCONEH
124	US UNEMPLOYED (16 YRS & OVER) VOLA	1	2	USUNPTOTO
125	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
126	WD COMMODITY PRICES: FOOD NADJ	1	2	WDI76EXDF
127	WD COMMODITY PRICES: NON-ENERGY NADJ	1	2	WDI76NFDF
128	WILSHIRE 5000 TOTAL MARKET - PRICE INDEX	1	2	WIL5TMK
	JAPAN			
1	BD HWWA INDEX OF WORLD MARKET PRICES OF RAW MATS, EURO AREA NADJ	1	2	BDHWWAINF
2	EK REAL EFFECTIVE EXCHANGE RATES - CPI BASED VOLN	1	1	EKOCC011
3	JP OPERATING RATIO - MANUFACTURING SADJ	1	1	JPCAPUTLQ
4	JP CPI: ALL ITEMS LESS FOOD(LESS ALCOHOLIC BEV)& ENERGY(CORE)	0	1	JPCPCOREF
5	JP CPI: ALL ITEMS LESS FRESH FOOD NADJ	0	1	JPCPIEFAF
6	JP BASIC DISCOUNT & LOAN RATE (ODR PRIOR TO JAN 01)	0	1	JPDISCRT
7	(SA) JP EFFECTIVE JOB APPLICANTS VOLN	1	1	JPEFFAPPF
8	JP EMPLOYED PERSONS (METHO BREAK MAR 2011) VOLA	1	1	JPEMPTOTO
9	JP EMPLOYMENT INDEX OF REGULAR EMPLOYEES - ALL INDUSTRIES VOLA	0	1	JPEPAIREG
10	JP EXPORT PRICE INDEX - ALL COMMODITIES NADJ	1	1	JPEXPPRCF
11	JP INTEREST-BEARING GOVERNMENT BONDS - 10-YEAR (EP)	0	1	JPGBOND.
12	(SA) JP HOURS WORKED INDEX - CONSTRUCTION VOLN	1	1	JPHACSREH
13	JP NEW HOUSING CONSTRUCTION STARTED (AR) VOLA	1	1	JPHOUSE.O
14	JP IMPORT PRICE INDEX - ALL COMMODITIES NADJ	1	1	JPIMPPRCF
15	JP INDL. PROD. OF FINISHED GDS - CAP. GDS VOLA	0	1	JPIPCAPGG
16	JP INDL. PROD. OF FINISHED GDS - CONSUMER GDS VOLA	0	1	JPIPCONGG
17	JP INDL. PROD. OF FINISHED GDS - FINAL DEMAND GDS VOLA	0	1	JPIPFINDG
18	JP INDUSTRIAL PRODUCTION - MINING & MANUFACTURING VOLA	0	1	JPIPTOT.G
19	JP RATIO OF EFFECTIVE JOB OFFERS PER ONE APPLICANT VOLA	0	1	JPJOBAPPE
20	JP LEADING INDICATORS - CONSUMER CONFIDENCE INDEX NADJ	0	1	JPLEDCCIR
21	JP MONEY SUPPLY: M1 (METHO-BREAK, APR. 2003) CURN	1	1	JPM1....A
22	JP MONEY SUPPLY: M2 (METHO-BREAK, APR. 2003) CURA	1	1	JPM2....B
23	JP NEW JOB APPLICANTS VOLA	1	1	JPNEWAPPO
24	JP NEWLY ISSUED GOVERNMENT BONDS YIELD (10 YEARS) NADJ	0	1	JPNISGBY
25	JP NIKKEI BOND INDEX YIELD - LONG-TERM (EP) NADJ	0	1	JPNKBNDLF
26	JP NIKKEI BOND INDEX YIELD - MEDIUM-TERM (EP) NADJ	0	1	JPNKBNDMF
27	JP NIKKEI BOND INDEX YIELD - SHORT-TERM (EP) NADJ	0	1	JPNKBNDSF
28	JP MACHINERY ORDERS CURA	1	1	JPNOTOTLB
29	JP CLI SPREAD OF IRS (NORMALISED) SADJ	1	1	JPOL2055E
30	(SA) JP MONTHLY WORKERS SAVINGS & INSURANCE RATE NADJ	0	1	JPPERSAV
31	JP INDL. PROD. OF FINISHED GDS - PRODUCER GDS VOLA	0	1	JPPRODCPG
32	JP DOMESTIC CORPORATE GOODS PRICE INDEX(DCGPI) NADJ	1	1	JPPROPRCF
33	JP DOMESTIC CORPORATE GOODS PRICE INDEX(DCGPI) NADJ	1	2	JPPROPRCF
34	JP INDL. PRDN. OF GDS.: CNSTR. GDS. - CONSTRUCTION VOLA	1	1	JPPSCONCG
35	JP RETAIL SALES VALUE SADJ	0	1	JPRETSALE
36	JP TOKYO STOCK EXCHANGE - TOPIX (EP) NADJ	1	1	JPSHRPRCF
37	(SA) JP SALES: LARGE SCALE RETAIL STORES - GOODS CURN	1	1	JPSLRSGDA
38	JP UNEMPLOYMENT RATE (METHO BREAK MAR 2011) SADJ	0	1	JPUN%TOTQ
39	JP JAPANESE YEN TO US $	1	1	JPXRUSD.
40	JP JAPANESE YEN REAL EFFECTIVE EXCHANGE RATE INDEX NADJ	0	1	JPXTW..RF
41	JP JAPANESE YEN NOMINAL EFFECTIVE EXCHANGE RATE INDEX NADJ	0	1	JPXTWBJNF
42	NYSE COMPOSITE - PRICE INDEX	1	2	NYSEALL
43	S&P 500 COMPOSITE - PRICE INDEX	1	2	S&PCOMP
44	spread	0	1	spread
45	UK MONTH AVERAGE SPOT EXCHANGE RATE, EUR INTO USD VOLN	0	2	UKAERD..P
46	UK LONDON GOLD PRICE - P.M. FIXING (EP)	1	2	UKGOLDP.
47	US CPI - ALL URBAN: ALL ITEMS SADJ	1	1	USCONPRCE
48	US FEDERAL FUNDS RATE (MONTHLY AVERAGE)	0	1	USFDFUND
49	US TREASURY BILL RATE - 3 MONTH (EP)	0	1	USGBILL3
50	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA	1	2	USHOUSE.O
51	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA	1	2	USIPTOT.G

52	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ	1	2	USSHRPRCF
53	US STANDARD AND POORS' 500 COMPOSITE - DIVIDEND YLD	0	2	USSPDIVY
54	US UMICH CSS: CONSUMER SENTIMENT - EXPECTATIONS VOLN	1	1	USUMCONEH
55	US UNEMPLOYED (16 YRS & OVER) VOLA	1	2	USUNPTOTO
56	WD COMMODITY PRICES: CRUDE OIL NADJ	1	2	WDI76AADF
57	WILSHIRE 5000 TOTAL MARKET - PRICE INDEX	1	2	WIL5TMK

Table B4: Data Employed for the Estimation of DSGE Models

	US
INV	Investment Account, Private Fixed Investment, Overall, Total, Current Prices, AR, SA, United States Dollar, BEA - Bureau of Economic Analysis, U.S. Department of Commerce
CONS	Personal Outlays, Personal Consumption Expenditure, Overall, Total, Constant Prices, AR, SA, United States Dollar, 2009 Chained Prices, BEA - Bureau of Economic Analysis, U.S. Department of Commerce
OUT	GDP: National Product Account, Gross Domestic Product, Overall, Total, Constant Prices, AR, SA, USD, 2009 chnd prices, USGDP...D; Spurce: U.S. Bureau of Economic Analysis (BEA)
PRICES	GDP Deflator: Implicit Price Deflator, Gross Domestic Product, Total, SA, Index, 2009=100, USGDPIPDE, Source: U.S. Bureau of Economic Analysis (BEA)
HOURS	Hours Worked Per Employee, AR, SA, Volumes, OECD Economic Outlook,copyright OECD
WAGES	Earnings, Hourly, Non-Farm Business, Real Hourly Compensation, Non-Farm Business, Index, SA, Index, 2009 = 100, Bureau of Labor Statistics, U.S. Department of Labor
POP	Population (Estimates Used in National Accounts), BEA - Bureau of Economic Analysis, U.S. Department of Commerce
RATE	United States, Federal Funds Rate (Monthly Average), Federal Reserve, United States
EMP	United States, Employed Population, Aged 15 and Over, Employment, All Persons (Ages 15 and Over), SA, Main Economic Indicators,copyright OECD
	UK
INV	Gross Fixed Capital Formation (Chained Volume Measure), SA, British Pound Sterling, 2011 Chained Prices, ONS - Office for National Statistics, United Kingdom
CONS	Final Consumption Expenditure, Households, Household and Non-Profit Institutions Serving Households's Expenditure, Constant Prices, SA, British Pound Sterling, 2011 Chained Prices, ONS
OUT	GDP: British Pound Sterling Chained DOM GDP GRS MKT Mrkt PRC PRD TOT, UKGDP...D, Source: ONS
PRICES	GDP Deflator: Implicit Price Deflator, Implicit Price Deflator, GDP at market prices, SA, Index, 2009=100, UKGDPIPDE, Source: ONS
HOURS	United Kingdom, Hours Worked Per Employee, Volumes, seasonally adjusted, AR, SA, N/A, UKOCFHRBO, Source: ONS
WAGES	Gross Domestic Product Components, Compensation of Employees, Income Approach, Total, Current Prices, SA, British Pound Sterling, ONS - Office for National Statistics, United Kingdom
POP	United Kingdom, Population, Population Aged 16-64, SA, ONS - Office for National Statistics, United Kingdom
RATE	United Kingdom, Interest Rate, Central Bank Policy, Bank of England
EMP	Employed Employees Labour Force, United Kingdom, Employment, SA, Oxford Economics
	Euro Area
INV	Gross Investment, The AWM Database
CONS	Private Consumption, The AWM Database
OUT	GDP (Real) , The AWM Database
PRICES	GDP Deflator, The AWM Database
WAGES	Compensation to Employees, The AWM Database
POP	Labour Force (persons), The AWM Database
RATE	Euro Zone, Interest Rate, Central Bank Policy, ECB
EMP	Total Employment (persons), The AWM Database

Note: For Output, Investment, Consumption, transformation applied is $\Delta 100*(\log(x_t/POP_t))$ when the series are in current prices and $\Delta 100*(\log((x_t/Prices_t)/POP_t))$ when the series are in current prices. For wages, the transformation is $\Delta 100*(\log(Wages_t))$ if compensation data are constant prices and $\Delta 100*(\log(Wages_t/Prices_t))$ if compensation data are current prices. For inflation, the applied transformation is $\Delta 100*(\log(Prices_t))$; and for the Policy rate: RATE/4. Finally, for hours worked, the transformation is $h_t=100*\log(Hours_t*(Emp_t/Emp_{BASE\ YEAR}))/Pop_t)$-mean(h). For the Eurozone, due to unavailability of data on hours, we augment the model with an equation linking employment and hours and use data on employment, by linearly detrending 100*log employment series.